Developing a Model-Based Lane Change Decision Aid System by Integrating Driver Uncertainty

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Abstract

As a complex and highly dynamic driving task, the lane change maneuver is considered as one of the most dangerous driving maneuvers. It requires drivers to integrate highly dynamic information from different sources to make a safe decision and to perform the maneuver safely in a timely manner. Driver uncertainty about the current situation can substantially prolong this decision-making process, potentially leading to dangerous lane change maneuvers. Regarding traffic safety, it is therefore essential to consider driver uncertainty while developing lane change assistance systems. In addition, the information that existing lane change assistance systems provide to the drivers is not adaptive to drivers’ uncertainty states during decision-making in a current situation. Without taking driver uncertainty into account, this non-adaptive assistance can be either obtrusive with too many unnecessary advice or too unobtrusive without providing needed information on time. For instance, when drivers are quite certain about the situation and systems still provide information actively, the interaction with such systems can be annoying and even disturbing. When drivers are uncertain during the decision-making process and systems provide no helpful information on time, the interaction with the systems will be not beneficial. Such non-adaptive aids may have an impact on drivers’ mental models of the system functionality and further decrease driver trust in assistance systems. As a consequence, it can result in the disuse of such systems. Hence, it is also important to build driver trust in automation with the consideration of driver uncertainty while developing lane change assistance systems in addition to providing traffic safety.

The “emancipation” theory of trust states that humans tend to trust in their partners when they are uncertain in social interaction. Inspired by this, it is assumed that in the context of human-machine interaction, drivers tend to build trust in systems and to avoid the occurrence of system disuse, when systems consider driver uncertainty and help to shorten the decision-making process and the decision times accordingly. Based on this assumption, this dissertation aims to develop a Model-Based Lane Change Decision Aid System (MBLCDAS) integrating driver uncertainty during decision-making in its interaction strategy for lane change maneuvers. The MBLCDAS adapts its information behavior to driver uncertainty: Information will be given in an active way when drivers are uncertain during decision-making, and information will be presented unobtrusively when drivers are certain. This adaptive assistance can help build appropriate trust in the assistance system and also provide traffic safety.

To develop the MBLCDAS, first driver uncertainty during decision-making has been studied in a driving simulator for specific lane change scenarios on two-lane motorways. The distance gap, closing speed and time to collision (TTC) between the subject vehicle and approaching vehicle are varied and found to significantly influence driver uncertainty. Reaction times, subjective uncertainty scores and the action proportion for lane change decisions are used to measure driver uncertainty. With a frequency of 60 Hz in the driving simulator, information of current traffic situations concerning distance gap, closing speed and the resulting TTC between the subject vehicle, the lead vehicle,
and the approaching vehicle is collected and then used to develop a probabilistic model of driver uncertainty.

Regarding the attributes for the model of driver uncertainty, \(TTC_A\) (respectively \(TTC_B\)) and \(G_A\) (respectively \(G_B\)) that separately represent the TTC between the subject and the lead vehicle (respectively the approaching and the subject vehicle), the distance gap between the subject and the lead vehicle (respectively the approaching and the subject vehicle) are selected based on the mutual information. For the outputs of the model, the collected subjective uncertainty scores from the driving simulator experiment are mapped onto the conceptualized two uncertainty states of the MBLCDAS based on the Kullback-Leibler Divergence. Regarding the structure of the model, Tree-Augmented Naive (TAN) Bayesian classifier is selected among the candidate models (full Bayesian classifier, naive Bayesian classifier, TAN classifier) with the highest Bayesian Information Criterion (BIC) score. After learning the structure and parameters of a TAN Bayesian classifier, the conditional probability of the driver uncertainty in a given lane change situation can be inferred. The developed model of driver uncertainty is then evaluated with test data, showing an average accuracy of approximate 0.78.

Based on the selected decision thresholds, the inferred probability of driver uncertainty can be classified into the driver’s uncertainty state as either “certain” or “uncertain”. In addition, with the help of the action threshold between the subject and the approaching rear vehicle, the recommendation for lane change decisions can be classified as either “decision for changing the lane” or “no lane changes decision” by a safety analysis. The classified driver’s uncertainty state and the classified recommendation for lane change decisions together trigger the Human Machine Interface (HMI) via symbols representing different levels of criticality and driver uncertainty. Emotional faces consisting of the dimensions of colors and emotional expressions are chosen as symbols: Colors describe criticality as well as driver uncertainty, while emotional expressions provide recommendations for lane change decisions.

After implementing the model of driver uncertainty and the corresponding HMI in the driving simulator, the developed MBLCDAS has been then evaluated with 20 participants. In the evaluation study, the MBLCDAS has been compared with other reference systems with respect to the reduction of reaction times and the building of trust. The results show that all systems including the MBLCDAS are able to reduce reaction times in comparison to the driving without any assistance. In addition, trust has been built in the MBLCDAS. Compared to other reference systems without considering driver uncertainty, the MBLCDAS is reported to be most accepted and trusted by participants.
Publication

Parts of this thesis have been already published in the following proceedings:


- Yan, F., Eilers, M., Baumann, M., Lüdtke, A. (2016, October). Development of a Lane Change Assistance System Adapting to Driver’s Uncertainty During Decision-Making. In Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications Adjunct (pp. 93-98).

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1 Introduction

The development of computer and automation technology has greatly changed our way of life since the 1940s, from smart mobile phones to autopilots in the aviation domain or Advanced Driver Assistance Systems (ADAS) in the automotive domain. Especially in the automotive domain, the development of automation technology has extremely influenced the interaction between drivers and ADAS. Following the six levels (Level 0 - Level 5) of driving automation proposed by the Society of Automotive Engineers (SAE) [127], car manufacturers aim to develop ADAS with higher levels of automation functions to support drivers while driving, such as vehicles with more than two automated functions (Level 3 or even higher) or even fully autonomous cars (Level 5). With the increasing level of automation, ADAS begin to actively take over more driving tasks. Subsequently, the relationship between drivers and ADAS has entered into a phase of cooperation, where ADAS may need to understand drivers by recognizing drivers’ states and then aid drivers with appropriate suggestions. In this way, ADAS are able to cooperate with drivers through presenting the helpful information. However, if the assistance systems do not consider drivers’ states, the assistance that systems provide may not be appropriate and considered as non-adaptive. This non-adaptive assistance can be either obtrusive with too many unnecessary advice or too unobtrusive without needed information on time. It can impact on drivers’ mental models of the system functionality [124], which indicates that drivers may be confused with the functionality of the systems, if the systems give inappropriate aids without adapting to drivers’ current states. Moreover, this inappropriate aids can further influence driver trust in assistance systems [17] as well as the disuse of systems [116]. To give an example, if the assistance provided by the systems is too annoying or not given when needed, drivers will tend not to trust the systems. Consequently, they will probably turn off the assistance systems. For that reason, it is essential to develop ADAS that can adapt to drivers’ states and cooperate with drivers.

This thesis is constructed in the context of developing ADAS that can adapt to driver state and cooperate well with drivers. Specifically speaking, it aims to develop a lane change assistance system that adapts to the drivers’ uncertainty states during decision-making in lane change maneuvers, to support drivers and facilitate the building of trust in the assistance system.

This chapter consists of 6 sections. In section 1.1, the motivation of the thesis is introduced, followed by the research objective (section 1.2). In sections 1.3 and 1.4, the research approach and the thesis overview are presented. In section 1.5, main contributions are summarized. At the end of this chapter, the relevant publications for the thesis (section 1.6) are listed.

1.1 Motivation

With the growth of passenger and commercial vehicles in the last 25 years, traffic safety regarding fatal injuries or deaths has become an important issue. The lane change maneuver is ranked as
one of the most dangerous driving maneuvers [56]. According to the latest statistics of the German Federal Statistical Office [23], about 6 percent of traffic accidents with injured or killed persons on extra-urban roads (inclusive motorways) in 2015 are caused by lane change maneuvers. The lane change maneuver is a complex and difficult driving task that requires lateral and longitudinal control in parallel. To execute a lane change maneuver, drivers have to integrate highly dynamic information perceived from various sources and then make safe decisions within a very restricted time frame. Driver uncertainty is assumed to play an important role in decision-making processes in lane change situations. Based on the definition of uncertainty in the decision-making context [66], driver uncertainty [171] in this thesis is defined as:

“Driver's difficulty to make appropriate decisions of either changing the lane or not in a given lane change situation”.

Driver uncertainty about the current lane change situation can substantially prolong the decision-making process [119], which potentially leads to dangerous lane change maneuvers. With respect to traffic safety, it is essential to consider driver uncertainty during decision-making while developing lane change assistance systems.

Additionally, various driver assistance systems (e.g., Blind Spot Warning System, Automatic Braking System) have been developed to support drivers in completing the driving tasks related to perception, decision making or operation [150]. Specific to the lane change maneuver, Lane Change Decision Aid System (LCDAS) [70] with Blind Spot Warning function can help drivers detect the blind spot. The Closing Vehicle function can help drivers detect the approaching vehicle in the adjacent lanes. In addition, the Lane Change Warning function combines both functions. The problem of these lane change assistance systems is that they do not consider the drivers’ uncertainty states about the current traffic situation and may provide inappropriate advice to drivers. For example, when drivers are certain about the current lane change situation and know what they need to do, the frequently presented information by the system can be annoying and even disturbing. Another instance can be that when drivers are uncertain during the decision-making processes, there is no helpful information provided on time. Although these systems are helpful with regard to road safety, the provided assistance without considering driver uncertainty is not adaptive. These non-adaptive aids may have an impact on driver mental model of the system functionality [124] and further lead to driver distrust in assistance systems [17]. As a consequence of distrust in systems, it results in the disuse of these systems [116]. Therefore, it is also essential to build appropriate trust in systems with the consideration of driver uncertainty while developing lane change assistance systems, in addition to providing traffic safety.

To the author’s knowledge, there is no lane change assistance system that considers driver uncertainty during decision-making. Coping with problems of existing LCDAS that do not consider drivers’ uncertainty states, a lane change assistance system that considers and adapts to driver uncertainty during the decision-making process is proposed for two purposes. First, the proposed system aims to reduce driver uncertainty during decision-making in difficult lane change situations to provide road safety. Second, the proposed system aims to help build driver trust in the system by adapting the system information to driver uncertainty.
1.2 Research Objective

The research objective of this thesis is to develop a Model-Based Lane Change Decision Aid System (MBLCNAS) \(^1\) that adapts its information behavior to driver uncertainty during the decision-making in lane change situations. The MBLCNAS is supposed to help drivers with useful information timely when drivers are uncertain during their decision-making processes, and be unobtrusive when drivers are certain in lane change maneuvers. In this way, traffic safety during lane change maneuvers is expected to be improved and appropriate driver trust in lane change assistance systems is also expected to be built.

1.3 Research Approach

A schematic overview of the structure of the MBLCNAS is shown in Figure 1.1 [173]. It can be seen that four components are defined in this structure. Due to the lack of using any behavioral marker of driver uncertainty as inputs for the model, situation factors that influence driver uncertainty in lane change maneuvers are investigated [175] as a starting point (refers to “Traffic Situation” in Figure 1.1) of the proposed MBLCNAS. The primary component for the proposed MBLCNAS is a model of driver uncertainty [172] (refers to “Model of Driver Uncertainty” in Figure 1.1). The model can classify drivers’ uncertainty states as either “certain” or “uncertain” in a given lane change situation by evaluating relevant factors of the traffic situation that are assumed to be related to driver uncertainty. Another component of the structure is the “Decision Recommendation” (see Figure 1.1) that gives suggestions for lane change decisions which are communicated via the “Human Machine Interface (HMI)” (see Figure 1.1) taking also drivers’ uncertainty states from the model into account [171].

![Figure 1.1: A schematic overview of the structure of the proposed MBLCNAS.](image)

\(^1\)In this thesis, the use of term “Model-Based Lane Change Decision Aid System” (MBLCNAS) is equal to “lane change assistance system that adapts to driver uncertainty during the decision-making”.

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*Figure 1.1: A schematic overview of the structure of the proposed MBLCNAS.*
1 Introduction

Following this schematic structure, a systematic human factors approach regarding the development of MBLCDAS is sequentially described in the following four steps:

- **Step 1: Investigating Driver Uncertainty during Decision-Making in Lane Change Maneuvers.** Two driving simulator experiments are conducted to investigate driver uncertainty during decision-making in lane change situations. In the first experiment, the impact of distance gap ² between the subject vehicle and the rear approaching target vehicle on driver uncertainty on German motorways is investigated in lane change maneuvers [175]. In the second experiment, the influences of closing speed ³ and time to collision (TTC) ⁴ between the subject vehicle and the rear vehicle on driver uncertainty in lane change maneuvers are examined.

- **Step 2: Developing A Model of Driver Uncertainty during Decision-Making in Lane Change Maneuvers.** Based on the empirical data collected from the driving simulator study (Step 1), relevant factors that influence driver uncertainty are selected as attributes for the model of driver uncertainty [172]. Theses selected attributes are then used to develop a probabilistic model that can infer the probability of drivers' uncertainty states in a given lane change situation [172].

- **Step 3: Developing A Model-Based Lane Change Decision Aid System that Adapts to Driver Uncertainty.** The developed model of driver uncertainty is integrated into a lane change assistance system in the driving simulator, which enables the MBLCDAS to classify drivers' uncertainty states as either "certain" or "uncertain" in a given lane change situation [171]. In addition, decision recommendations based on drivers' subjective preferences are used to suggest appropriate lane change decisions to provide traffic safety [171]. The model of driver uncertainty and the decision recommendation together trigger corresponding symbols displayed on the HMI [171].

- **Step 4: Evaluating the Model-Based Lane Change Decision Aid System.** After developing the MBLCDAS, an evaluation study in a driving simulator is conducted. The MBLCDAS is compared to other reference systems that do not consider driver uncertainty regarding the reduction of reaction times and the building of trust [173].

1.4 Thesis Overview

This thesis consists of six chapters including the introduction (Chapter 1) and the theoretical background as well as research questions (Chapter 2), main contributions regarding the development of Model-Based Lane Change Decision Aid System (Chapters 3-5) plus a concluding chapter (Chapter 6). The thesis’s structure is shown in Figure 1.2 and an overview of all research chapters is given below.

²For the definition of distance gap, see section 3.1: Definition.
³For the definition of closing speed, see section 3.1: Definition.
⁴For the definition of TTC, see section 3.1: Definition.
1 Introduction

- **Chapter 1: Introduction.** The first chapter mainly gives the introduction of this thesis, including sections of motivation, research objective, research approach, thesis overview, main contributions, and relevant publications.

- **Chapter 2: Theoretical Background.** The second chapter aims to give a description of the theoretical background of this thesis. It consists of sections of human information processing, uncertainty, uncertainty and trust, automation, modeling driver behavior and Bayesian Network. Based on the theoretical background, research questions and research hypotheses are introduced in the end.

- **Chapter 3: Investigating Driver Uncertainty in Lane Change Maneuvers.** This chapter presents two driving simulator studies about investigating driver uncertainty during decision-making on German motorways in lane change maneuvers [175], which is consistent with the Step 1 in the research approach. It includes sections of related work, research questions, the first study of investigating the influence of distance gap on driver uncertainty, and the second study of investigating the influences of TTC and closing speed on driver uncertainty.

- **Chapter 4: Developing a Model-Based Lane Change Decision Aid System.** This chapter presents the development of a model-based lane change decision aid system that adapts to both criticality and driver uncertainty during decision-making in lane change scenarios on simulated two-lane highways [172], which covers the Step 2 and Step 3 in the research approach. The first part of this chapter presents the development of a probabilistic model for recognizing drivers’ uncertainty states in lane change situations. In the second part of this chapter, the design of HMI is introduced, which is treated as an essential component of the proposed MBLCDAS. This chapter consists of sections of concept and structure of the MBLCDAS, developing a probabilistic model of driver uncertainty, decision recommendation, Human-Machine Interface, implementation, and a summary.

- **Chapter 5: Evaluating a Model-Based Lane Change Decision Aid System.** An evaluation study comparing the proposed MBLCDAS and other reference systems that do not consider driver uncertainty is presented in this chapter [173]. It is investigated that if driver trust can be built and reaction times can be reduced with the developed MBLCDAS. This chapter is consistent with the Step 4 in the research approach and is composed of the related work, research goal and hypothesis, method, results, and summary.

- **Chapter 6: Conclusion.** The last chapter summarizes the whole thesis and discusses the open issues. It includes the sections of the summary of the thesis, contributions, open issues and the future work.
1.5 Main Contributions

The main contribution of this thesis is the systematic development of a MBLCDAS that adapts its information behavior to driver uncertainty during decision-making in lane change maneuvers (Chapter 3-5), which fills the gap of the current lane change assistance systems that do not consider driver uncertainty. Concretely, the development of the MBLCDAS that adapts to driver uncertainty is expected to contribute to the following aspects:

- **Empirical Aspect**: The experimental part of this thesis is expected to help understand driver
uncertainty during decision-making in lane change maneuvers, which is mainly addressed in Chapter 3. The factors that influence driver uncertainty and the measurement of driver uncertainty during decision-making in lane change maneuvers are explored, which can be used to empirically measure human uncertainty in general.

- **Methodology:** To develop a lane change assistance system that adapts its information behavior to driver uncertainty, this thesis has made use of fully empirical data derived from a driving simulator study to develop a probabilistic model for the MBLCDAS (Chapter 4). This applied human factors methodology combining the experimental methodology and Bayesian modeling can be applied to other domains for developing human-centered assistance systems.

- **Theoretical Aspect:** The “emancipation” theory of trust from social psychology has been applied to the driving context, which supplements to the theory of trust in automation with the building of driver trust by adapting to driver uncertainty. It can be generalized to other domains (e.g., aviation or maritime domains) to help build human trust in automation.

- **Practical Aspect:** The proposed MBLCDAS considers both criticality and driver uncertainty, which supplements to the existing lane change decision aid systems that only consider criticality by aiding drivers with warnings. The approach of developing MBLCDAS can be generalized in other domains to help developing assistance systems coping with human uncertainty. Especially, the addressed driver uncertainty is meaningful to mixed traffic scenarios in the context of automated driving in future, where vehicles with human drivers and fully automated vehicles without human drivers interact with each other. The driver uncertainty model can be extended to the context of automated driving, to help automated vehicles recognize driver uncertainty and make the communication between drivers and automation transparent.

### 1.6 Relevant Publications

Parts of this thesis have been presented in the following research papers:


  This paper contributes to Chapter 3 relating to the experiment design of the studies that investigate driver uncertainty during decision-making in lane change maneuvers.


  This paper is conducive to Chapter 1 with regard to the research approach.

This paper partly contributes to Chapter 3 (Step 1) with respect to the first driving simulator study about the investigation of driver uncertainty during decision-making in lane change maneuvers.


  This paper favors Chapter 4 regarding the development of the model of driver uncertainty.

- Yan, F., Eilers, M., Baumann, M., Lüdtke, A. (2016, October). Development of a Lane Change Assistance System Adapting to Driver’s Uncertainty During Decision-Making. In Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications Adjunct (pp. 93-98).

  This paper gives rise to Chapter 4 concerning the Human Machine Interface design of the developed MBLCDAS.


  This paper plays a role in Chapter 5 respecting the evaluation study of the developed MBLCDAS that adapts to driver uncertainty.
2 Theoretical Background

As a chapter introducing theoretical background for the proposed MBLCDAS in lane change maneuvers, chapter 2 begins with the human information processing (section 2.1), in which drivers' difficulty during decision-making in lane change maneuvers is discussed. In section 2.2 “Uncertainty”, the influence of human uncertainty on the decision-making process, the definition, type and source of driver uncertainty are introduced. The influence of uncertainty on trust is introduced in section 2.3 “Uncertainty and Trust”. Followed is a section 2.4 “Automation”, in which types and levels of automation as well as the Lane Change Decision Aid Systems (LCDAS) are introduced. To develop the proposed MBLCDAS, the model-based approach including Bayesian networks is introduced in the section 2.5 “Modeling Driver Behavior and Bayesian Network”. In the last section 2.6, research questions and research hypothesis are presented based on the theoretical background.

2.1 Human Information Processing

Information processing plays a key role in human performance, which is critical for understanding the prediction and modeling of human-system interaction [160]. While interacting with systems in different situations, humans go through different stages of information processing, from the perception of the information from the environment, the transformation of the perceived information, to the resulting actions based on the interpreted information. There are mainly three approaches to information processing: traditional open-loop representation from cognitive psychology describing distinct stage sequences, the ecological approach emphasizing the integrated flow of information through the human, and the approach of cognitive engineering emphasizing the understanding of experts’ knowledge structures [160]. Summarizing literature about how humans perceive and process information, Wickens [161] proposed a generic model of information processing which is later adopted as a framework of the information-processing model (see Figure 2.1) [162].
2 Theoretical Background

Figure 2.1: Model of human information processing [163, p. 4].

The four-stage information processing model is under the influences of the memory model and two vital elements (attention and feedback). Amounts of stimuli from the environment are perceived by the sensory system and may be shortly stored in the Short Term Sensory Store (STSS) [163]. Only parts of the stimuli are interpreted after perception based on past experiences, which are stored in the long-term memory [163]. After perception, the interpretation of the situation can trigger an immediate response, which is shown at the bottom in Figure 2.1. Another path of information processing from perception to response action is to go through working memory which can temporarily store and process the information with cognition [163]. With the cognitive function of working memory, the information stored in the working memory can be carried out in long-term memory for future use. As two vital elements, feedback may provide new sensory information for the response execution in a situation, while attention can filter the sensed and perceived information and supply energy to the information processing at different stages [163].

As a simplification of Wickens’ human information-processing model, Parasuraman et al. [115] proposed a four-stage model, which includes the stages of sensory processing, perception, decision making, and response selection (see Figure 2.2). At the stage of sensory processing, various information is registered by sensory receptors and pre-processed. The processed information will be perceived and manipulated in the second stage followed by cognitive operations. Based on the cognitive processing, decisions are made at the third stage. Consistent with the decision, response or action is implemented at the final stage.

Figure 2.2: The four-stage model of human information processing [115, p. 287].
In the driving context, in order to make an appropriate decision with the corresponding action for dynamic driving tasks, drivers usually need to first perceive information from their surrounding traffic situations. Then they interpret the perceived information and execute a maneuver with actions according to the decision made by drivers. Specific to the lane change maneuver, drivers perceive information from their surrounding environment (such as the lead vehicle or approaching vehicles in the side mirror). Afterwards, they interpret the perceived information and assess, if the current situation allows a safe lane change maneuver. In the end, they make lane change decisions and react with actions of either steering left for changing a lane or waiting.

NHTSA has stated that human factors contribute to 94 percent of traffic crashes and the first two critical reasons attributed to drivers are recognition errors (41%) and decision errors (33%) [139]. Especially, drivers’ poor observations and misjudgments of other vehicles’ speeds, locations and of distances during decision-making can result in inadequate lane change behaviors [28, 50, 42]. This indicates that drivers have difficulties in the perception and decision-making processes while changing lanes.

2.2 Uncertainty

The humans’ decision-making processes usually involve uncertainty and risk. Moreover, most important decisions involve uncertainty rather than risk [21], which implies the important role of uncertainty in the decision-making. This section aims to give an introduction of uncertainty in the context of the decision-making: The influence of uncertainty on decision-making is introduced in section 2.2.1, followed by the definition, type and source of uncertainty in section 2.2.2. Finally, driver uncertainty is defined and its distinction from other sources of uncertainty is described in section 2.2.3.

2.2.1 The Influence of Uncertainty on Decision-Making

The investigation of uncertainty is notable in the decision-making literature [73, 96]. Moreover, many researchers have shown that uncertainty obstructs the effectiveness of decision-making [146, 111, 22]. Uncertainty is usually conceptualized as subjective experiences [35]. Unconventionally, uncertainty is conceptualized in terms of its impact on the action: “uncertainty in the context of action is a sense of doubt that blocks or delays action” [88, p. 150]. The relationship of uncertainty and delayed action was described well by March, who made a comparison between consequential action and obligatory action based on the two generic decision-making models [95]. For the consequential action, the decision-making model requires decision makers to overcome the doubts about alternatives, outcomes, and the relative attractiveness of the outcomes. For the obligatory action, decision makers need to pay attention to the situation and the role that they play in this situation [95].

In the driving context, driver uncertainty in lane change maneuvers can prolong drivers’ decision-making process and induce long reaction times [119], which potentially leads to dangerous lane change crashes. According to March, the action that drivers need to execute after estimating the alternatives during decision-making can be categorized as consequential action. As drivers are uncertain during decision-making and they spend long time on comparing the outcomes of possible alternatives. As a consequence, they react very late with long reaction times.
2.2.2 Definition, Type and Source of Uncertainty

“Uncertainty occurs where the decision-maker has to estimate or infer the probabilities of the various outcomes happening (for example, placing a bet on a racehorse or the chances of the weather being sunny for a barbecue at the weekend)” [21, p. 15]. The early conceptualizations of uncertainty in behavioral decision theory came from Anderson et al.: “A situation in which one has no knowledge about several states of nature has occurred or will occur” or “A situation in which one knows only the probability of which of several possible states of nature has occurred or will occur” [10, p. 238]. Generally, uncertainty is defined as “a realization that our beliefs and representations of the world are unable to accurately predict future events in our environment” [109, p. 1]. “In behavioral and cognitive sciences, uncertainty has mainly been defined within the scope of decision-making and therefore refers to a difficulty to predict events that are the consequences of our actions” [109, p. 2].

Yu and Dayan [11] proposed two basic types of uncertainty: expected and unexpected uncertainty. Expected uncertainty means “environments in which available information is a weak predictor of future events”; unexpected uncertainty refers to “a situation where fundamental changes in the environment invalidate past predictions” [109, p. 2]. Expected uncertainty is usually known and relatively stable. Another distinction is made between aleatory uncertainty and epistemic uncertainty: aleatory uncertainty refers to “objective and irreducible uncertainty about future occurrences that is due to inherent stochasticity in physical or biological systems”, and epistemic uncertainty is referred to as “subjective and reducible, because it results from a lack of knowledge about the quantities or processes identified with a system” [158, p. 131]. Another classification of uncertainty is based on what decision makers are uncertain about, which are the doubts about alternatives, outcomes of alternatives, or situations [88].

Three basic sources of uncertainty are incomplete information, inadequate understanding, and undifferentiated alternatives [88]. In most cases, uncertainty occurs when the information for making decisions are incomplete [140]. Lacking the needed information and overloaded by the conflicting meanings of information, decision makers have an inadequate understanding of the information and can not react appropriately [159]. The third source of uncertainty occurs when decision makers understand perfectly, but cannot differentiate between the alternatives [88].

2.2.3 Driver Uncertainty

Driver uncertainty for this thesis is defined based on the definitions of uncertainty in behavioral and cognitive sciences reviewed above. Compared to the general definition of uncertainty that refers to the difficulties in predicting events, the addressed driver uncertainty does not focus on the difficulty of predicting events, but emphasizes the difficulty to make lane change decisions. This is due to the consideration of the specific drivers’ information processes in lane change maneuvers and also the addressed driver uncertainty during the decision-making process. As a reference, Hick [62] and Hyman [67] use “temporal uncertainty” to describe the aspect of response selection. Based on these, driver uncertainty during decision-making in lane change maneuvers is defined as:

“Driver’s difficulty to make appropriate decisions of either changing the lane or not in a given lane change situation”.

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According to the introduced types of uncertainty, driver uncertainty in this thesis is supposed to be the expected uncertainty and epistemic uncertainty. An example of expected uncertainty is although drivers have learned how to execute lane change maneuvers in the driving school, they are still uncertain about the appropriate lane change decisions in some lane change situations. Regarding epistemic uncertainty, driver uncertainty is subjective and is supposed to be reduced through the help of an assistance system. Besides, according to the proposed classification of uncertainty by Lipshitz and Strauss, driver uncertainty can be considered as the doubts about alternatives [88].

Regarding the source of the addressed driver uncertainty, it refers to the source of uncertainty “undifferentiated alternatives” [88]. According to drivers’ information processing in the lane change maneuvers, drivers usually perceive the relevant traffic information and make adequate interpretations in the perception process. Based on the third source of uncertainty “undifferentiated alternatives” [88] mentioned above, drivers still have difficulties to distinguish from two alternatives during the decision-making process: changing the lane or waiting in the given lane change situation, although information can be perfectly understood in the perception process. Accordingly, driver uncertainty in this thesis exclusively refers to the difficulties to make lane change decisions during the decision-making process after the perception process in lane change maneuvers.

In addition, distinctions should be made between the addressed driver uncertainty and other kinds of driver uncertainty, such as driver perception uncertainty that occurs in the perception process or event uncertainty 1 etc. Driver perception uncertainty can arise from the bad weather conditions or from errors in perceiving moving images [137]. Sheu [136] is one of the pioneering researchers who associated uncertainty in perceived relative speed with driver behavior in the car following maneuver. Because of the judgment errors in perceiving moving images, he stated that the perception of speed (PRS) was somehow related to the focal point of vision [137]. He focused on the uncertainty of PRS and found that the relative speed and reaction time were two important factors for driver perception uncertainties in car following [137]. He assumed that there was a trade-off relationship of uncertainty in perceived relative speed and reaction time exists in car following and tested it using qualitative analysis, which explained the car-following phenomena under the influence of driver-perception uncertainty [137]. In addition to driver perception uncertainty, event uncertainty has also been studied in the driving context. Assuming that event uncertainty affects reaction time [62], the braking time including perception-reaction time and brake-movement time can be examined by event uncertainty varying among different situations where the response to the onset of a lead vehicle’s brake lights was required [156]. It was found that as uncertainty increased, perception-reaction time increased significantly, while the brake-movement time did not change [156]. Furthermore, it is noted that driver uncertainty is not the uncertainty about the interaction partners, e.g., the speed or the intention of the approaching vehicle in lane change maneuvers.

2.3 Uncertainty and Trust

The interaction between operators and automation is largely dependent on trust in automation [84], which implies the importance of considering the building of trust while developing assistance systems. A definition of trust specific for human-machine interaction is proposed by Lee and See [85].

1 It refers to the uncertainty about the lead vehicle’s brake actions.
and trust is defined as [85, p. 54]:

“The attitude that an agent will help achieve an individual’s goal in a situation characterized by uncertainty and vulnerability.”

This definition of trust clearly indicates the important influence of uncertainty on trust, which is summarized in this section. It starts with the factors influencing trust in automation (section 2.3.1). Then the important role of uncertainty on the building of trust is summarized in section 2.3.2. In the last section 2.3.3, the calibration of trust with regard to driver uncertainty is described.

2.3.1 Factors Influencing Trust in Automation

Marsch and Dibben have summarized the factors that influence trust by layers of trust (Figure 2.3), which are dispositional trust, learned trust, and situational trust [98]. This three layers of trust are then reviewed by Hoff and Bashir [65]. Dispositional trust including factors of culture, age, gender and personality traits refers to an individual’s long-term tendency to trust the automation under both biological and environmental influences, and is independent of the specific context or system [65]. Learned trust refers to the operator’s evaluations of systems based on the past experience, preexisting knowledge, automation’s performance or design features [65]. Situational trust is dependent on both the environment and context-dependent variations as well as the operator’s mental states [65]. Two main sources of variability in situational trust are the external environment and the internal, context-dependent characteristics of the operator [65]. External variability includes system’s type, complexity, task difficulty, workload, perceived risks, perceived benefits, organizational setting, and the framing of work [65]. Concerning internal variability, self-confidence, expertise, mood, and attentional capacity can also affect situational trust in automation [65].
2 Theoretical Background

Although uncertainty is supposed to play an important role in trust building reflected by the definition of trust [85], it is not considered in any of these three categories in Marsch and Dibben’s model after reviewing the relevant factors that influence trust in automation [65].

An attitude or expectation that is similar to uncertainty has been listed in the Marsch and Dibben’s model, which is called self-confidence [65]. Self-confidence is an important factor in decision making and also in the trust formation as well as reliance [85]. It is considered as a situational factor with regard to the internal variability that influences trust [98]. As a reference, the addressed driver uncertainty in this thesis describes both the external environment that induces uncertainty and also internal characters like humans’ subjective uncertainty. According to this, driver uncertainty can be classified as a situational factor, which is supposed to influence driver trust in automation.

2.3.2 Uncertainty and Trust

The importance of uncertainty in the facilitation of building of trust has been reported in many contexts. In real-life situations, Coleman emphasizes that although embeddedness, social capital and reputation play an important role in facilitating trust, other factors especially uncertainty may also facilitate trust [30]. For instance, he states that “the most extreme case of a need to place trust is that of a person in a desperate situation from which he cannot extricate himself without help” [30, p. 107]. In the formulation of exchange relations, Kollock states that the variation of uncertainty in
The form of information asymmetries has a significant influence on the level of trust: High uncertainty concerning the exchanged good will lead to high commitment with the partners who seem to be trustworthy and also high trust [78]. Hoff and Bashir state that “trust is needed when something is exchanged in a cooperative relationship characterized by uncertainty” [65, p. 409].

In the context of distributed reputation systems allowing all users to rate each other in online communities, decision-making under uncertainty is needed to select one agent among all possible interaction partners and this selection process can be supported by trust by using previous experience [13]. One of the factors that influences trust is the level of uncertainty that is associated with a transaction partner [13]. In the context of human machine interaction, Lee and See give the definition of trust that describes the relation of trust and uncertainty: “the attitude that an agent will help achieve an individual’s goal in a situation characterized by uncertainty and vulnerability” [85, p. 54], which suggests that the importance role of uncertainty in the building of trust in automation.

In the context of human machine interaction, a usual approach to conceptualize human trust in automation is to generalize the concept of trust in humans to “trust in automation” [85]. In addition to the work of Coleman [30] and Kollock [78] that analyses the relationship between uncertainty and trust, “emancipation” theory of trust in social psychology gives the inspiration of building trust from the perspective of uncertainty. The “emancipation” theory of trust states [170, p. 170]:

“General trust (trust in others in general) and commitment formation are considered alternative solutions to the problems caused by social uncertainty.”

The term “social uncertainty” refers to the risk of being exploited in social interactions. This social uncertainty encourages the formation of commitment with a particular partner and reduces the risk of being deceived in interacting with unfamiliar people. However, the formative commitment limits the choice for finding better opportunities existing outside the current relationship. By showing general trust, people can emancipate from the committed relationships and therefore have large opportunities [170]. General trust (trust in others in general) can be understood as “the default expectations of others’ level of trustworthiness” [170, p. 172], which is similar to the description of trust “as a stable personality trait” [85, p. 57]. Based on the statements that commitment formation can emancipate people from social uncertainty and general trust can emancipate people from committed relationships, it can be inferred that general trust can emancipate people from the social uncertainty. It means that when people are uncertain in the social interaction and have a general trust in others, they are able to reduce their uncertainty by trusting other people.

Another aspect that has an impact on trust in social interaction is if the partners seem to be trustworthy [78]. Keren’s [76] experiments show that people prefer an overconfident forecaster predicting with high probabilities of rain to a more accurate forecaster with low probabilities, which indicates that people with more confidence seem to be more trustworthy. As an illustration, imagine you arrive in a foreign city and want to look for the booked hotel. Without any maps or other navigation aids, you have no idea how to reach the hotel. Since you are very uncertain, you may stop a passerby and ask him/ her for the right way to the hotel. If (s)he behaves like being very sure about the answer (e.g., looks very confident and answers very fast), you will likely trust him/ her to set yourselves free from the uncertainty. Otherwise, when the passerby seems very uncertain about the advice, you will probably not tend to trust him/ her and ask another person again.

Extending the emancipation theory of trust with the consideration of the partners’ confidence states, it can be formulated that: When people are uncertain in social interaction while their partners are
2. Theoretical Background

certain, they tend to trust in their partners. Transferring it into the interaction between humans and machines, it is assumed that when humans are uncertain and the machine can provide useful information at that time to help to reduce their uncertainty, they tend to demonstrate trust in the machine. Specific to the context of driving in lane change maneuvers, it is assumed that when drivers are uncertain in lane change situations and assistance systems are quite certain to provide drivers with useful information, drivers will show a general trust to assistance systems to reduce their uncertainty.

2.3.3 Calibration of Trust

Trust in automation has an influence on reliance and the use of automation [114]. The perceived automation reliability is important to the calibration of trust [164], which further influences the use of automation [116]. In the context of automation, calibration is “the correspondence between a person's trust in the automation and the automation's capabilities” [85, p. 55]. Calibrated trust means that trust matches the system's capabilities and it will further lead to appropriate use. In other words, well calibrated trust in automation is “in direct proportion to its reliability” [164, p. 404]. Not well calibrated trust is considered as mistrust, which happens “when trust is not directly related to reliability” [164, p. 404]. The relation between reliability, trust, and use of automation is summarized in Figure 2.4 [164].

![Diagram of the relation between reliability, trust, and use of automation](image)

Figure 2.4: The relation between reliability, trust and use of automation. The “+” and “-” indicate separately the positive and negative effects [164, p. 406].

Distrust in automation is “a type of mistrust where the person fails to trust the automation as much as
appropriate” [164, p. 404], which will further lead to the disuse of automation. Distrust can also lead to inefficiency [164] or even real danger [141], due to the rejection of helpful advice offered by the automation. Overtrust in automation refers to complacency and happens when people have more trust in automation that it guarantees and usually has extreme negative effects [164]. If operators overtrust automation, they will fail to monitor information appropriately and are likely to be out of loop [14, 105]. Complacency has influences on operators’ detection, situation awareness, and skill loss. For example, operators tend to detect a failure slowly when they overtrust the automation [164]. When operators are out of the loop and do not know the ongoing states of the automated processes, they are unlikely to monitor and intervene adequately [129]. Another consequence of complacency is the operator’s degraded skills after using the automated system for a long time [164].

One important factor that contributes to not well calibrated trust is the non-adaptive assistance from automation [63]. The non-adaptive assistance may have an impact on drivers’ mental model of the system functionality [124], which further leads to the not well calibrated trust, especially drivers’ distrust in assistance systems [17]. As a consequence, drivers tend to disuse these systems [116]. Especially, the inappropriate alarm timing without considering driver state will influence driver performance and driver trust [4, 5, 7]. For instance, warnings that traditional lane departure warning systems provide are triggered by raw data and have been reported too reactive, as it does not consider the appropriate alarm timing based on driver state and driver performance [32]. The similar problem has also been reported by Wiese and Lee: Poorly timed warnings can increase driver workload and affect driver performance [165].

Regarding the addressed driver uncertainty in this thesis, it is assumed that lane change assistance systems without considering drivers’ uncertainty provide non-adaptive support, which may affect driver trust in systems and also the use of systems. To give an example, the non-adaptive assistance can be considered as too obtrusive providing too many unnecessary advice while drivers are quite certain about what they need to do in the current situation, or as too unobtrusive without needed information in time when drivers are quite uncertain during decision-making in lane change maneuvers. As a result, drivers may be confused with the functionality of the systems, which further leads to the not well calibrated trust, specifically driver distrust in assistance systems [17]. As a consequence of distrust in systems, these systems are disused by drivers [116]. Therefore, it is essential to calibrate appropriate trust between drivers and systems by adapting its information behavior to the drivers’ uncertainty states while developing lane change assistance systems.

In the driving context, many studies have shown the negative influence of the assistance without considering drivers’ uncertainty states on driver trust. If drivers are certain without the need of help and assistance systems still continuously provide advice, it will influence driver trust and the use of systems. For instance, the continuously displaying information of night vision systems will not be preferred by some drivers, as they only use night vision systems when they cannot see clearly and ignore systems when they can see very well [149]. Regarding the use of forward collision warning systems, when drivers are certain and can recognize the danger themselves of the preceding traffic, systems will be turned off by one-third of participants [38]. Similarly, when drivers have made their decisions before the forward collision warning alarm, trust is also reported to be decreased in the following alarms [6]. It implies that when drivers are certain, the assistance the lane change assistance system provide should not be too active, in order not to be annoying and even disturbing to further affect driver trust in systems. On the other hand, when driver are uncertain during lane decisions, the assistance should be given in an active way based on the introduced “emancipation”
2 Theoretical Background

theory of trust, in order to help drivers on time and build driver trust in automation. Hence, to well calibrate trust in the proposed lane change decision aid system, the provided support should be adaptive to drivers’ uncertainty states: When drivers are certain, information should be given in a conservative way; when drivers are uncertain during lane change decisions, the assistance should be given on time in an active way.

2.4 Automation

The term of automation was firstly introduced in the context of manufacturing. With the development of computer technology, nowadays automation is more understood as computers or automated systems that “interpret inputs, record data, make decisions, or generate displays including the sensors that go with them ” [134, p. 9]. A similar understanding of automation is from Lee and See: “technology that actively selects data, transforms information, make decisions, or controls processes ” [85, p. 50]. “In the fullest contemporary sense of the term, automation refers to (a) the mechanization and integration of the sensing of environment variables (by artificial sensors; (b) data processing and decision-making (by computers); and (c) mechanical action (by motors or devices that apply forces on the environment) or “information action” by communication of processed information to people” [134, p. 9]. In the context of human machine interaction, automation can support human performance in many aspects, such as keeping operators away from dangerous tasks, largely reduces operator overload and training requirements or increases the precision and economy of operations [130]. Also, automation can extend human capacity especially in multitasking [164].

This section starts with the introduction of types and levels of automation (section 2.4.1). Then Advanced Driver Assistance Systems (ADAS) as well as Lane Change Decision Aid Systems (LCDAS) are presented in section 2.4.2.

2.4.1 Types and Levels of Automation

According to the four-stage model of human information processing (see Figure 2.2), automation can be applied to four classes of functions: “(1) information acquisition; (2) information analysis; (3) decision and action selection; (4) action implementation” [115, p. 288]. The function of information acquisition works on the sensed data in the first stage of human information processing, providing strategies for scanning, organizing the information with some criteria (e.g., highlighting), or filtering by selecting certain information [115]. The function of information analysis supports the extrapolation and prediction of the incoming information at a low level or the integration of the sensed information to augment the human perception and cognition at a high level [115]. With the function of decision and action selections, automation helps operators to select decisions among the alternatives by replacing human decision options with machine decisions or by varying levels of enhancement [115]. In the phase of action implementation, automation executes the selected action by replacing the human voice or hand [115]. Regarding the assistance in lane change maneuvers, aids in the perception process are needed to help drivers in perceiving the potential danger of the rear approaching vehicles, especially in the blind spot area. In addition, as drivers have difficulties in the
decision-making process, the assistance with the function of decision and action selection is especially essential to the development of lane change assistance systems. The direct execution of the brake by automation is also required in some situations, especially in urgent lane change situations where drivers do not execute braking actions timely.

Among the four different types of automation, the function of decision-making is very important and has been addressed by various assistance systems in many domains. Usually, the automation with the decision-making assistance has different levels varied from fully automated control to human control. The levels of automation were initially described by Sheridan [135]. The range of automation is from fully manual control to fully automated control, including decision supports with weak guidance, decision supports with strong guidance, decision and implementation support, and human supervision [135].

Specific to the stage of decision and action selection/implementation, eight levels of automation ranging from complete manual control to complete automatic control are summarized by Sheridan (see Figure 2.5) [134]. From level 1 to level 4 with the increased automation levels, humans still control the tasks. From the level 5, computers start to execute tasks. As the proposed MBLCDAS is supposed to support drivers’ decision-making process by suggesting a recommendation for the current lane change situation, the automation level of the the proposed MBLCDAS should be at level 3 (“The computer selects one way to do the task and ”) accordingly.

A Scale of Degrees of Automation

1. The computer offers no assistance; the human must do it all.
2. The computer suggests alternative ways to do the task.
3. The computer selects one way to do the task and executes that suggestion if the human approves, or allows the human a restricted time to veto before automatic execution, or executes automatically, then necessarily informs the human, or executes automatically, then informs the human only if asked.
4. The computer selects the method, executes the task, and ignores the human.

Figure 2.5: A scale of degrees of automation [134, p. 62].

The design of the level and the type of automation is greatly dependent on the context during operation, which is known as adaptive automation [115]. Adaptive automation means “the control of functions shifts between humans and machines dynamically, depending on environmental factors, operator workload, and performance” [69, p. 147]. Later many concepts of adaptive automation appear, which mainly state that the interaction between humans and automated systems should adapt to the task or contextual demands [54, 113, 123, 114, 103, 106]. The empirical study of the adaptive automation was initially done in the Adaptive Function Allocation for Intelligent Cockpits (AFAIC) program, which then led to amounts of empirical research on the impact of adaptive automation on performance benefits and costs [69, 55]. The benefits of adaptive automation have been found in many empirical studies in the driving context [128]. For example, a real-time workload estimator presenting the information of the current traffic situation was developed to reduce the driver's workload
2 Theoretical Background

[120]. Lee et al. [83] developed warning functions for brake pulse, based on the classification of the driver’s brake duration and magnitude. Besides, adaptive automation can improve the driver’s inattentiveness with real-time assessment of driver visual behavior [153].

Concerning the proposed MBLCDAS, it is expected to provide adaptive automation that adapts its information behavior to driver uncertainty states: Information will be given unobtrusively when drivers are certain during decision-making, while information will be given in an active way timely when drivers are uncertain in lane change situations. With this adaptive assistance, driver trust is supposed to be built in the proposed MBLCDAS.

2.4.2 Lane Change Decision Aid Systems (LCDAS)

Based on the levels of automation or assistance, various Advanced Driver Assistance Systems (ADAS) have been developed in the driving context. ADAS are systems embedded in vehicles using sensors as well as signal processing to detect the vehicle environment and then collect relevant infrastructure-based data used for evaluation, to improve safety, driving comfort and driver’s workload, traffic efficiency and the environment [99]. Based on the levels of assistance and driving tasks, an overview of the assistance provided by ADAS is summarized in Figure 2.6 [68]. The levels of assistance consist of lateral or longitudinal control, information and warnings for avoiding collisions. Driving tasks include environment detection, decision making, and implementation of the action, according to the sequent phases of driving. Following the levels of assistance, a detailed description of the aids of ADAS are listed:

**N/A:** Without any assistance from ADAS, drivers need to detect and recognize the elements in the environment and make decisions about possible risks in a given situation, and then react with actions with the aim of reducing risks [64].

**Level 1:** At Level 1 of ADAS, ADAS mainly provide information collected from sensors and assists drivers with the detection of relevant information to enhance driver’s perception of the environment. For instance, Night Vision Systems can support drivers at night via a Heads-Up Display (HUD) based on infrared sensors and the thermal imaging technology [64]. However, they don’t provide any warnings of the potential risks.
2 Theoretical Background

Figure 2.6: A behavioural model of a driver and level of driver assistance [68, p. 4].

**Level 2**: At Level 2, ADAS support drivers not only in detecting the environment, but also in assessing the criticality of hazards by warnings, such as Lane Departure Warning (LDW) systems, which give warnings to drivers when the vehicle is out of its lane.

**Level 3**: In addition to Level 1 and Level 2, the ADAS at Level 3 can assist drivers through vehicle control without the input of drivers, in order to avoid hazards actively. The Adaptive Cruise Control (ACC) detects vehicles in front of drivers and intervenes to make sure that safe distances with the lead vehicle are not exceeded. The Level 3 ADAS can be used both in a normal situation such as ACC or in an abnormal situation, such as emergency mitigation braking that is used to reduce severity if the crash cannot be avoided [68].

The current LCDAS are at Level 2 in which they help drivers detect the environment and provide warnings if hazards or potential dangers are detected. In complement to the existing LCDAS, the proposed MBLCDAS additionally considers driver uncertainty to help drivers make lane change decisions. It means that the proposed MBLCDAS should provide an assistance of Level 2 to support drivers’ environment detection for hazards or dangers and decision making with the consideration of driver uncertainty. On the one hand, the proposed MBLCDAS can detect and assess the criticality of the lane change situations to provide traffic safety; on the other hand, it can provide adaptive lane change decisions depending on the drivers’ uncertainty states in the given lane change situations, to help build trust in the proposed MBLCDAS.
With reference to the traffic safety and driver uncertainty, the proposed MBLCDAS should provide an assistance of Level 2 supporting drivers’ environment detection for hazards or dangers and decision making with the consideration of the driver uncertainty. It can detect and assess the criticality of the lane change situations to provide traffic safety. In addition, it can provide appropriate decision recommendations depending on the drivers’ uncertainty states in the given lane change situations, in order to support drivers to make lane change decisions. According to the ISO standard 17387 “Lane Change Decision Aid Systems” (LCDAS) [70], there are mainly three lane change assistance systems: The LCDAS with the “Blind Spot Warning” function, the LCDAS with the “Closing Vehicle Warning” function and the LCDAS with the “Lane Change Warning” function. The LCDAS with the “Blind Spot Warning” function monitor the blind spot on the left and right adjacent to the driver’s own vehicle and give warnings to drivers, if the blind spots are occupied by any objects. The LCDAS with “Closing Vehicle Warning” function monitor the adjacent lanes to the left and right behind the driver’s own vehicle to detect vehicles approaching from behind. The LCDAS with “Lane Change Warning” function combine both of these functions. In the market, systems with “Blind Spot Warning” are available from Ford, Mercedes-Benz, Nissan/Infiniti, Peugeot, and Volvo [16]. Systems with “Lane Change Warning” are available from Audi, BMW, Mazda, and VW [16]. These current lane change assistance systems are mostly based on sensors, radars, images from the video or the wireless technology to provide warning functions for the potential risk and dangers [26, 20, 154, 97, 110, 102, 144], which support drivers with the problems mainly associated with the perception process during the lane change maneuver.

In addition, Habenicht et al. [53] developed a maneuver-based lane change assistance system to provide drivers with the recommendations of timing, direction and acceleration or deceleration for the lane change through the whole lane change maneuver. A Cooperative Lane-Change Assistant (C-LCA) in the EU FP7 project D3CoS² has been developed to assist the driver in finding an appropriate gap for changing the lane [75]. Concerning dynamics and characteristics of individual driver/vehicle, a personalized driver/vehicle lane change model for ADAS has been developed to provide personalized recommendations to drivers, which is found to increase potential acceptance and use of ADAS after the evaluation [24]. However, these lane change assistance systems do not take drivers’ uncertainty states into account.

To the author’s knowledge, there is no lane change assistance systems that especially consider driver uncertainty during decision-making in lane change maneuvers. As introduced above, driver uncertainty in lane change maneuvers can prolong the decision-making process and induce long reaction times [119]. In addition, assistance systems without considering drivers’ uncertainty states have great influence on driver trust in lane change situations. Hence, it is necessary to develop a lane change assistance system that considers driver uncertainty during decision-making to provide traffic safety and build driver trust in lane change maneuvers.

### 2.5 Modeling Driver Behavior and Bayesian Network

To develop a lane change assistance system that adapts to driver uncertainty, a model-based approach is used. The precondition for the proposed MBLCDAS that can classify drivers’ uncertainty

²http://www.d3cos.eu/.
states in given lane change situations is a model of driver uncertainty. This section first introduces
the modeling driver behavior in general (section 2.5.1) and then give a detailed introduction of the
Bayesian network (section 2.5.2).

2.5.1 Modeling Driver Behavior

Since the focus of automobiles has changed from vehicles to the driver since the middle 1950s,
lots of demands on modeling driver behaviors have been addressed, such as general human driver
skills and characters, specific drivers concerning age, experience etc., and portraying features [121].
In order to improve traffic safety and driving experience, driver behavior has been modeled to pre-
dict driving maneuvers, driver state and intent, vehicle and environmental factors, and to improve
transportation [8]. Modeling driver behavior means to “construct the mathematic model of driver
behavior and estimate the parameter of the model by analyzing the signals of sensors equipped
on the vehicle” [169, p. 663], which is usually integrated into the ADAS of the vehicles [8]. Con-
cerning the dynamics between the driver, the vehicle, and the environment, a framework to model
driver behavior with three layers (see Figure 2.7) including a sensing phase, a reasoning phase, and
an application layer has been introduced [8]. In the sensing phase, various inputs from the driver,
vehicle, and the environment are collected including the Controller Area Network (CAN), sensors,
and cameras [8]. After a reasoning process, the sensed data can be modeled for some applications
such as lane changing assistance, intersection decision-making, driver preference profiling, route
planning etc. In the last phase, these applications should be personalized in the future.

![Figure 2.7: Driver behavior modeling (DBM): sensing, applications, and future systems [8, p. 2].](image)

The driver behavior models can be divided into driver behavior analysis models and driver behavior
prediction models [82]. The driver behavior analysis models recognize a set of performed actions
by drivers to ensure the driver’s safety. They include hidden Markov models (HMMs), driver steering
models, models based on the vehicle on board diagnostic information and Add Boost Algorithm,
and design and implementation of driving behavior. The driver behavior prediction models infer the
drivers’ future behaviors from the driver’s current actions, visual behavior, and traffic environment etc. They consist of probabilistic models, improved driver behavior models, acceleration models (car following models, neural network models, Gazis–Herman–Rothery (GHR) models, fuzzy logic Models), gap acceptance models, lane change models, dynamic driver behavior models, collision models, collision avoidance models, linear models, and point based models [82].

Besides, AbuAli et al. [8] have classified the reactive models and predictive models: Reactive models are usually used to learn the maneuver or the observed driver’s behavior after conducting the action, while predictive models need to recognize driver’s actions in real time, which is essential for ADAS in which actions should be immediately performed.

Concerning the algorithms and approaches to model driver behavior, statistical models, discriminative models, and generative models are commonly used. Statistical models are used to study the driver’s behavior with model fitting and regression techniques. Because statistical classification approaches are intuitive in general, they are limited to classify multidimensional data [12]. To cope with the basic classification’s limitation, discriminative approaches such as Support Vector Machines (SVMs) are used. The generative models study the underlying patterns in the collected data and determine the probabilities of a set of outputs for a given model [8]. One example is the Bayesian network (BN), which is a probabilistic graphical model in which nodes represent random variables, and the (lack of) arcs represent conditional independence assumptions [107].

### 2.5.2 Bayesian Network

In order to model driver uncertainty based on the available traffic information from the environment referring to Figure 1.1, a reasoning system is needed to extract drivers’ uncertainty states. As one of the reasoning algorithms, a model-based method in which our knowledge of how the system works is encoded in a computer-reasonable form, is taken into account [77]. As the model-based approach has a separation of knowledge and reasoning and a general set of reasoning algorithms can be generated, it can apply any model in every domain [77]. However, our ability to observe and model the world is limited, different possibilities while reasoning need to be considered. Based on probability theory, probabilistic models which consider multiple possible outcomes and their associations can better reflect the real world [77]. Probabilistic models are called Bayesian networks within the field of cognitive science and artificial intelligence [118]. As a probabilistic graphical model based on directed acyclic graph (DAG), Bayesian network use a graph-based representation (nodes and edges) to effectively construct and utilize the relevant attributes [77]. Nodes represent proportional variables of interest and edges represent informational dependencies among the variables. The dependencies can be quantified by conditional probabilities for each node given its parents [125]. A simple Bayesian network is illustrated in Figure 2.8. It consists of variables Toothache, Cavity, Catch, and Weather, which are represented with nodes. It can be seen that Weather is independent of the other three variables, as there are no links between them. The absence of a link between Toothache and Catch indicates conditional independence between them, given Cavity. In contrast, Cavity directly causes Toothache and Catch with the links between them.
Figure 2.8: A simple Bayesian network: Weather is independent of the other three variables and Toothache and Catch are conditionally independent, given Cavity. [125, p. 511].

Regarding the semantics of Bayesian networks, it can be represented as the joint probability distribution (JPD). The used notations are defined as follows: variables can be specified using upper-case letters; sets of variables can be specified using bold upper-case letters; assignments to variables can be specified using lower-case letters; sets of assignments to sets of variables can be specified using bold lower-case letters etc. A Bayesian network is defined as a directed acyclic graph (DAG) that codes a joint probability distribution over a set of variables \( X = \{X_1, ..., X_n\} \). The vertices of a DAG \( G \) represent the random variables in \( X \) and its arcs represent the (in)dependencies between these variables where each variable \( X_i \in X \) is independent of its non-descendants, given a set of parents \( Pa(X_i) \) and a set of parameters \( \theta \) quantifying the probabilities of the Bayesian network. It is assumed that \( \theta \) consists of a parameter \( \theta_{x|Pa(X)} = P(x|Pa(X)) \) for \( x \in X \) and \( Pa(X) \in Pa(X) \).

Given \( G \) and \( \theta \), a BN defines a unique JPD over \( X \) as:

\[
P_G(X) = \prod_{i=1}^{n} P(X_i|Pa(X_i)).
\]

(2.1)

Bayesian networks have many advantages, compared to other relevant models, such as a Markov network, which is also probabilistic graphical model but using an undirected graph [77]. The Markov network is usually used for image processing and it is difficult to represent directed dependencies among variables with Markov networks [118]. Besides, another special probabilistic model is logistic regression, which is a linear regression classifier and can be represented by a BN. However, the discriminative logistic regression cannot deal with the unlabeled data, whereas Bayesian networks can deal with the uncertain or incomplete data caused by the vibration of the vehicle or noise etc. [108]. In addition, with the Bayesian network’s transparency, its semantics and properties can be easily understood and evaluated [172]. All parameters of the model can be interpreted in terms of probabilities, which can help understand and evaluate the model.

In the driving context, Bayesian networks have been widely used for detecting and predicting driver behavior, in order to help develop intelligent driver assistance systems that consider drivers’ psy-
2 Theoretical Background

Cognitive functions. For example, driver fatigue can be recognized based on the dynamic Bayesian network, information fusion and multiple contextual and physiological features [176]. McCall and Trivedi used a probabilistic model to predict the driver's intent to brake, the need for braking given the current situation based on varying levels of situational severity and driver attentiveness and intent [101]. Besides, driver decelerating intentions can be predicted using a Bayesian network in terms of traffic conditions and driver types at unsignalized intersections [9]. In addition, a Bayesian network was developed to estimate driver unusual behavior when approaching a specific intersection with a stop sign, which can be further used for warning presentation [81]. Eilers et al. [37, 36] proposed a Bayesian Autonomous Driver Mixture-of-Behaviors model to model driver longitudinal control behavior in an inner-city traffic scenario, which can be used for prototyping intelligent assistance systems. Regarding modeling lane change behavior, driver behavior at the time of lane change can be inferred using Bayesian networks by capturing time-series steering angle data [143]. The recognition of typical lane change maneuvers in structured highway scenarios can be modeled with object-oriented Bayesian networks [74]. Driver lane changing behavior can be analyzed based on parallel Bayesian networks [89].

According to the introduced categories of driver behavior models, the model of driver uncertainty recognizing drivers' uncertainty states can be treated as a driver behavior analysis model. For the model of driver uncertainty, it is important to induce the directed dependency of driver uncertainty from relevant variables. Based on the introduced advantages of the Bayesian network and its applications in the driving context, a Bayesian network is chosen to induce the drivers' uncertainty states based on the relevant variables during decision-making in lane change maneuvers.

2.6 Research Questions and Hypotheses

After integrating the model-based approach into the research objective, the research objective can be formulated as the development of a Model-Based Lane Change Decision Aid System (MBLCAS) that adapts to drivers’ uncertainty states, to provide traffic safety and also build driver trust in the system. Based on the research objective and theoretical background above, four research questions and the corresponding research hypothesis can be derived in this thesis.

Driver uncertainty in lane change situations can lead to long reaction times [119], which is very dangerous for the time-demanding lane change maneuver. To develop a lane change decision aid system that can adapt to the drivers’ uncertainty states, firstly it is important to investigate when drivers are uncertain during decision-making in lane change maneuvers, which will be addressed by RQ 1:

- **RQ 1**: When are drivers uncertain during the decision-making process in lane change maneuvers?
  - **RQ 1a**: Does the distance gap between the subject vehicle and the rear approaching vehicle influence driver uncertainty in lane change maneuvers, when the closing speed between the subject vehicle and the rear approaching vehicle is constant?
  - **RQ 1b**: Do both closing speed and time to collision (TTC) between the subject vehicle
2 Theoretical Background

and the rear approaching vehicle influence driver uncertainty in lane change maneuvers?

Factors such as distance gap, closing speed, and TTC that can generally reflect the criticality of lane change situations or influence the decision-making process will be considered, and their influences on driver uncertainty will be studied. Regarding the research hypothesis of RQ 1, distance gap, closing speed, and TTC are all expected to have significant influences on driver uncertainty and further to help explore when driver uncertainty appears during decision-making in lane change maneuvers ($H_1$).

After investigating driver uncertainty and developing the proposed MBLCDAS, it would be interesting to know whether the proposed MBLCDAS can reduce drivers’ long reaction times in lane change maneuvers regarding traffic safety mentioned in research objective. This will be addressed by RQ 2:

- **RQ 2**: Compared to driving without assistance systems, can the proposed Model-Based Lane Change Decision Aid System (MBLCDAS) that adapts to driver uncertainty reduce drivers’ long reaction times during decision-making in lane change maneuvers?

It is assumed that with the MBLCDAS that can infer drivers’ uncertainty states during decision-making, driver uncertainty can be reduced in terms of the reduction of reaction times, compared to the driving without assistance systems ($H_2$).

The RQ 3 addresses the building of trust between drivers and the proposed MBLCDAS described in the research objective:

- **RQ 3**: Can trust be built between drivers and the proposed Model-Based Lane Change Decision Aid System (MBLCDAS) that adapts to driver uncertainty?

Inspired by the “emancipation” theory of trust that describes the relationship between the social uncertainty and trust [170] in social psychology, it is assumed that when drivers are uncertain in their decision-making processes and systems can help them reduce their uncertainty with useful advice timely, they tend to build trust in systems. As the MBLCDAS adapts to driver uncertainty and is supposed to aid drivers when they are uncertain, trust is assumed to be built in the MBLCDAS ($H_3$).

RQ 4 addresses the comparison between the existing lane change assistance systems that do not consider driver uncertainty and the proposed MBLCDAS considering driver uncertainty:

- **RQ 4**: Is the proposed Model-Based Lane Change Decision Aid System (MBLCDAS) that adapts to driver uncertainty more trusted and accepted than comparable reference systems that do not consider driver uncertainty in lane change maneuvers?

It is assumed that the proposed MBLCDAS considering driver uncertainty is more trusted and accepted than other lane change assistance systems without considering driver uncertainty ($H_4$).

In order to answer the RQ 1, experiments that investigate driver uncertainty during decision-making in lane change maneuvers need to be conducted (Step 1 in chapter 1). For the research questions from RQ 2 to RQ 4 that concern traffic safety and the building of trust, the MBLCDAS should be developed under the model of driver uncertainty that is based on the collected information from experiments (Step 2, Step 3) and then evaluated (Step 4).
3 Investigating Driver Uncertainty in Lane Change Maneuvers

Because of the induced high cognitive workload [60] while executing parallel driving tasks (e.g., longitudinal control, lateral control, observing vehicles), the lane change maneuver is rated as one of the most dangerous and difficult driving maneuvers by drivers [56]. According to the statistics released by German Federal Statistical Office [3], 2.4 million traffic crashes with 3377 fatalities and 389535 injuries were recorded by the police in 2014. About 13 percent of traffic accidents with injured persons on German highways in 2014 occurred during lane change maneuvers. Accordingly, this thesis draws attention to the lane change maneuver.

With reference to the Step 1 in the research approach, chapter 3 presents two studies of investigating driver uncertainty during decision-making in lane change maneuvers. It consists of 6 sections. In section 3.1, the basic definitions of terms or variables related to the experiments are introduced. In section 3.2, the related work of driver behavior and factors influencing driver uncertainty in lane change maneuvers are reported, followed by the research questions in section 3.3. In sections 3.4 and 3.5, two studies about the influences of distance gap (Study I), closing speed and time to collision (Study II) on driver uncertainty during decision-making in lane change maneuvers are separately described.

3.1 Definition

- **Lane Change Maneuver**: A driving maneuver that moves a vehicle from one lane to another where both lanes have the same direction of travel [46]. One of the most common types of the lane change is a maneuver in which a driver changes lanes to pass a slower lead vehicle to maintain current speed [61].

- **Driver Uncertainty**: Drivers’ difficulty to make appropriate decisions of either changing the lane or not in a given lane change situation. It is noted that driver uncertainty exclusively refers to the difficulties during decision-making after the perception process.

- **Distance Gap**: Longitudinal distance along a traveled way, usually measured in feet or meters, between one vehicle’s leading surface and another vehicle’s trailing surface [126].

- **Closing Speed**: The difference between the subject vehicle’s speed and the approaching target vehicle’s speed [70].
• **Time To Collision**: The time required for two vehicles to collide, if they continue on their present speed and path [168], which is calculated as the distance between the two vehicles divided by their relative velocity (Δ V) [86].

• **Reaction Time**: Time interval, usually measured in seconds or milliseconds, from the onset of an initiating event to the first movement of the driver's hand (on the steering wheel) or foot (on a pedal or from the floor) [126].

### 3.2 Related Work

In order to investigate driver uncertainty in lane change maneuvers, factors that have an impact on driver uncertainty during decision-making in lane change maneuvers need to be found based on the related work. First, the investigations of driver behavior in lane change maneuvers are reviewed and summarized in section 3.2.1. It is followed by the factors that influence the driver’s decision-making in lane change maneuvers in section 3.2.2, from which the factors that potentially influence driver uncertainty in lane change maneuvers are drawn.

#### 3.2.1 Driver Behavior during Lane Change Maneuvers

As the overtaking maneuver usually includes a lane change maneuver, the literature of driver’s behavior during lane change maneuvers as well as in overtaking are reviewed. The early research of overtaking started from drivers’ judgments in the 1960s and researchers examined the needed length of road for overtaking, and overtaking in daylight and at night [31, 44]. In the 1980s, amounts of observational studies on drivers’ overtaking strategies, driving patterns, gender and exposure, speed, types of vehicles, and drivers’ beliefs regarding overtaking were carried out [166, 167, 56]. Since the 1990s, research using driving simulator has focused on the effect of gender and aggression on simulated driving [33, 100]. Later, overtaking intentions and overtaking sight distances, overtaking duration and distance, effect of driver age and gender, and overtaking assistance systems were examined [58, 15, 90, 40, 41]. Using a behavioral approach, many studies have investigated drivers’ gap acceptance and the corresponding influence factors in overtaking [43, 18]. However, the addressed driver uncertainty has not been studied in the lane change maneuvers.

#### 3.2.2 Factors influencing Driver Uncertainty during Lane Change Maneuvers

To study driver uncertainty during decision-making in lane change situations, factors influencing driver’s decision-making in lane change maneuvers and also overtaking have been considered based on the following findings. It was reported that drivers had difficulty in estimating accurately

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1 Overtaking is defined as any moving obstacle, which requires the driver to move out of lane and subsequently move back into lane in order to pass [117, p. 75]
the distance and speed of an approaching vehicle under the influence of certain perceptual factors [144, 52]. Silver and Bloom [138] reported that drivers had difficulties in estimating the distance of an approaching car, which was also later found by Gordon and Mast [50]. Farber and Silver [45] argued that drivers could accurately judge the distance of an approaching car, but not of the oncoming car’s speed, which implies the importance of velocity between the subject vehicle and an approaching vehicle during lane changing. In addition, Bella [18] found that TTC affected driver behavior in overtaking maneuvers on two-lane rural roads. The TTC between the lead car and approaching cars is important for visual judgments, initiation, and control of braking in overtaking [177, 168, 51, 145, 87]. These parameters are relevant for decision-making in overtaking as well as in lane change maneuvers and have been used to study the accuracy of drivers’ perceptual estimation and perceived risk. However, they have not been used to investigate driver uncertainty during decision-making in lane change maneuvers.

Summarizing these findings, distance gap, closing speed, and TTC between the subject vehicle and an approaching vehicle are important factors that impact on the driver’s decision-making in lane change maneuvers. Accordingly, they are chosen as factors that are supposed to potentially influence driver uncertainty during decision-making in lane change situations for the following experiments.

### 3.3 Research Question

This chapter aims to answer the first research question (RQ 1: When is the driver uncertain during lane change maneuvers?), which can be divided into the following two research questions:

- **RQ 1a** Does the distance gap between the subject vehicle and the rear approaching target vehicle influence driver uncertainty during decision-making, if the closing speed between the subject vehicle and the approaching target vehicle remains constant in lane change maneuvers?

- **RQ 1b** Do closing speed and TTC between the subject vehicle and the approaching target vehicle also influence driver uncertainty during decision-making in lane change maneuvers?

In order to answer the research question RQ 1, two experiments have been conducted in the driving simulator (see Figure 3.1) and they will be described in the following sections 3.4 and 3.5.

### 3.4 Study I: Investigating the Influence of Distance Gap on Driver Uncertainty

After reviewing the literature regarding factors that influence driver behavior during lane change maneuvers, it is assumed that distance gap, closing speed and TTC have a potential impact on driver uncertainty during decision-making in lane change maneuvers. The first experiment starts with simple lane change situations where the closing speed between the subject vehicle and the
approaching vehicle is constant. To answer RQ 1a above, it will investigate the influence of the distance gap between the subject vehicle and the approaching vehicle on driver uncertainty during decision-making in lane change maneuvers.

3.4.1 Participants

16 participants (9 female) recruited from the student pool of Carl von Ossietzky University of Oldenburg participated the first study and they had an average age of 24.6 years (SD = 11.9) [175]. They all had a valid German drivers license with an average of 7.0 years of driving experience (SD = 6.7). After the experiment, they were paid 10 euro for the 1-hour participation [175].

3.4.2 Apparatus and Driving Scenario

In order to study the influence of distance gap between the subject vehicle and the approaching target vehicle on driver uncertainty during decision-making in lane change maneuvers, a driving simulator experiment (see Figure 3.1) was conducted. The experiment was conducted in a fixed based driving simulator at the OFFIS- Institute for Information Technology [175]. A field of view of approximate 160 degrees was provided by three projection surfaces to simulate a 3D-environment, which was generated by the driving simulation software SILAB ². With SILAB, traffic simulation and various scenarios were simulated. The instruments and exterior mirrors were simulated and visualized on small LCD screens which were embedded in the mockup. In addition, a keypad was put near the center console (see Figure 3.3) [175].

Figure 3.1: The driver’s perspective at the beginning of the first experiment in the driving simulator.

²https://wivw.de/de/silab.
As one of the most common types of the lane change, a basic maneuver where a driver changes lanes to pass a slower lead vehicle [39, 61] was chosen. A two-lane German motorway track was simulated with SILAB. Adaptive Cruise Control (ACC) plus Lane Keeping Assistance (LKAS) were used to control the subject vehicle (A), which was set up in the right lane of the motorway [175]. The subject vehicle was held at a constant speed of 130 km/h and approached a slower lead vehicle (B) with a constant speed of 100 km/h in the right lane. Additionally, a third vehicle (C) (target vehicle) was approaching the subject vehicle with a constant speed of 140 km/h in the left lane (Fig. 3.2) [175].

![Figure 3.2: The simulated lane change scenario for the first experiment: The subject vehicle (A) driving at 130 km/h approaches a slower lead vehicle (B) driving at 100 km/h, while a faster rear target vehicle (C) driving at 140 km/h approaches the subject vehicle (A).](image)

### 3.4.3 Experiment Design

The independent variable is the distance gap between the subject vehicle and the approaching target vehicle [175]. The impact of the distance gap on driver uncertainty has been first studied in a pilot study [174], in which the distance gap was varied from 20 m to 48 m with 4 m interval [175]. In this experiment, the distance gap of 52 m is added, in order to have a coverage of the distance gaps that potentially impact on driver uncertainty [175]. Totally, there are 9 different lane change situations (from 20 m to 52 m with 4 m interval).

The dependent variables are reaction time, subjective uncertainty score and action proportion [175]. In the work of Petzold and his colleagues [119], it was reported that driver uncertainty was related to reaction times: The more uncertain the drivers were, the longer reaction time they had. It is expected that the manipulation of distance gaps will trigger different levels of driver uncertainty, which leads to the differences in reaction times. In addition, differences in subjective uncertainty scores and the action proportion are also expected under the manipulation of the distance gap.

A within-subject design with the repeated measure was used, which meant that each participant needed to do all experimental conditions [175]. Each participant had totally 288 trials, which were distributed in four blocks [175]. Each block contained 8 repetitions of 9 distance gaps, which were randomly assigned in each block and balanced within participants [175]. There was a 2-minute break between blocks and the whole experiment took about one hour [175].
3 Investigating Driver Uncertainty in Lane Change Maneuvers

3.4.4 Procedure

At the beginning of the experiment, an informed consent and a demographic survey were given to participants [175]. After reading the procedure and safety instructions, participants were then brought to the driving simulator. They were instructed to put their hands on the steering wheel and the right foot over the brake pedal, followed by a familiarization phase with 15 trials as an exercise [175].

Initially, participants were asked to look in front and observe the lead vehicle (B) [175]. An acoustic signal was given after 4.5 seconds and the approaching target vehicle (C) was set up at 9 different distances gaps (20 m to 52 m with 4 m interval), which were measured bumper to bumper [175]. At the same time, participants were asked to look at the left side mirror and make the decision to either change the lane, or stay in the lane behind the lead vehicle (B) [175]. Their actions were recorded either by steering left (about 20 degrees) indicating lane change decisions or braking indicating no lane change decisions [175].

After the selected action was executed, the lead vehicle (B) and the approaching target vehicle (C) disappeared from the scenario [175]. Participants were then instructed to rate their subjective uncertainty scores on a 5-point Likert scale from 1 to 5 (1 = very uncertain, 5 = very certain) on the keypad (see Figure 3.3) [175]. It was explained that the rating was not about the correctness of their decisions, but the difficulty they felt during their decision-making in the given lane change situation [175]. After typing the rating on the keypad, the scenario for next trial was initialized and the next trial began [175].

Figure 3.3: The driver is giving the subjective uncertainty score in the given lane change situation in the first experiment.

3.4.5 Results

The data collected from the simulator platform were preprocessed and saved in CSV (Comma Separated Values) format [175]. They were then analyzed in the free software environment for statistical
computing $R^2$ [175]. Concerning the experiment design, a repeated-measures one-way ANOVA with post-hoc tests is considered to test the significant effect of the distance gap on reaction times and subjective uncertainty scores [175]. Correspondingly, the results of the inferential statistics of reaction times, subjective uncertainty scores will be reported. In addition, the result of the descriptive statistics of the action proportion will also be reported.

The reaction time is the time measured between the acoustic signal (see section 3.4.4) and the action, while the subjective certainty score is recorded by the score rated by participants on the keypad after their actions [175]. The mean reaction times and mean subjective uncertainty scores for 9 distance gaps are shown in Figure 3.4. It can be summarized that that drivers react very quickly at small or large distance gaps with short reaction times (minimum of 1.04 s $\sim$ 1.32 s) and low subjective uncertainty score up to 4.27 $\sim$ 4.57 [175]. Drivers seem to be most uncertain at medium distance gap (36 m) with the highest uncertainty score of 3.41 and the longest reaction time of 1.63 s [175]. It is noticed that at the distance gap of 36 m, the mean reaction time and the mean uncertainty score reach their maximums [175]. Besides, the curve of the mean reaction time runs inversely to the curve of the mean uncertainty score [175].

![Figure 3.4](image)

For the reaction times, the sphericity cannot be assumed as the $p$-value of Mauchly’s test of sphericity is smaller than 0.05 [175]. Because the value of epsilon is above 0.75, the Huynh-Feldt correction for departure from Sphericity is considered [175]. The results indicate that there is a significant effect of the distance gap on reaction time, Wilks’s Lambda = 0.44, $F(8, 504) = 79.23, p < .001$ [175].

\[3https://www.r-project.org/.\]
The distance gap of 36 m is treated as interesting with the maximum reaction time and maximum subjective uncertainty score [175]. In the Tukey’s HSD test, it can be seen in Table 3.1 that the gap of 36 m is significantly different from other distance gaps except for distance gaps of 40 m and 44 m [175].

Table 3.1: Tukey’s HSD test of a repeated-measures one-way ANOVA of reaction times (**** 0.001, *** 0.01, ** 0.05, * 0.1, 1; LCL = Lower Control Limit for the mean; UCL = Upper Control Limit for the mean), first published in [175].

<table>
<thead>
<tr>
<th>Gap pair</th>
<th>Difference</th>
<th>LCL</th>
<th>UCL</th>
<th>P-value (Sig.)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.004</td>
<td>0.240</td>
<td>0.037.</td>
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<td>0.146</td>
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<td>0.000***</td>
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<tr>
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<td>0.345</td>
<td>0.581</td>
<td>0.000***</td>
</tr>
<tr>
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<td>0.474</td>
<td>0.710</td>
<td>0.000***</td>
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<td>0.415</td>
<td>0.652</td>
<td>0.000***</td>
</tr>
<tr>
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<td>0.367</td>
<td>0.604</td>
<td>0.000***</td>
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<tr>
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<td>0.000***</td>
</tr>
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<td>0.399</td>
<td>0.000***</td>
</tr>
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<td>0.352</td>
<td>0.588</td>
<td>0.000***</td>
</tr>
<tr>
<td>40-24</td>
<td>0.412</td>
<td>0.293</td>
<td>0.530</td>
<td>0.000***</td>
</tr>
<tr>
<td>44-24</td>
<td>0.364</td>
<td>0.245</td>
<td>0.482</td>
<td>0.000***</td>
</tr>
<tr>
<td>48-24</td>
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<td>0.162</td>
<td>0.398</td>
<td>0.000***</td>
</tr>
<tr>
<td>52-24</td>
<td>0.159</td>
<td>0.040</td>
<td>0.277</td>
<td>0.001**</td>
</tr>
<tr>
<td>32-28</td>
<td>0.199</td>
<td>0.081</td>
<td>0.317</td>
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</tr>
<tr>
<td>36-28</td>
<td>0.328</td>
<td>0.210</td>
<td>0.446</td>
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</tr>
<tr>
<td>40-28</td>
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<td>0.151</td>
<td>0.388</td>
<td>0.000***</td>
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<td>44-28</td>
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<td>0.340</td>
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</tr>
<tr>
<td>48-28</td>
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<td>0.020</td>
<td>0.256</td>
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</tr>
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<td>0.017</td>
<td>-0.101</td>
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<tr>
<td>36-32</td>
<td>0.129</td>
<td>0.011</td>
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</tr>
<tr>
<td>40-32</td>
<td>0.071</td>
<td>-0.048</td>
<td>0.189</td>
<td>0.648</td>
</tr>
<tr>
<td>44-32</td>
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<td>-0.096</td>
<td>0.141</td>
<td>1.000</td>
</tr>
<tr>
<td>48-32</td>
<td>-0.061</td>
<td>-0.179</td>
<td>0.057</td>
<td>0.804</td>
</tr>
<tr>
<td>52-32</td>
<td>-0.182</td>
<td>-0.301</td>
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<td>0.000***</td>
</tr>
<tr>
<td>40-36</td>
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<td>-0.177</td>
<td>0.060</td>
<td>0.838</td>
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<tr>
<td>44-36</td>
<td>-0.106</td>
<td>-0.225</td>
<td>0.012</td>
<td>0.118</td>
</tr>
<tr>
<td>48-36</td>
<td>-0.190</td>
<td>-0.308</td>
<td>0.072</td>
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</tr>
<tr>
<td>52-36</td>
<td>-0.311</td>
<td>-0.430</td>
<td>0.193</td>
<td>0.000***</td>
</tr>
<tr>
<td>44-40</td>
<td>-0.048</td>
<td>-0.166</td>
<td>0.070</td>
<td>0.944</td>
</tr>
<tr>
<td>48-40</td>
<td>-0.132</td>
<td>-0.250</td>
<td>0.013</td>
<td>0.016.</td>
</tr>
<tr>
<td>52-40</td>
<td>-0.253</td>
<td>-0.371</td>
<td>0.135</td>
<td>0.000***</td>
</tr>
<tr>
<td>48-44</td>
<td>-0.084</td>
<td>-0.202</td>
<td>0.035</td>
<td>0.407</td>
</tr>
<tr>
<td>52-44</td>
<td>-0.205</td>
<td>-0.323</td>
<td>0.087</td>
<td>0.000***</td>
</tr>
<tr>
<td>52-48</td>
<td>-0.121</td>
<td>-0.240</td>
<td>0.003</td>
<td>0.039.</td>
</tr>
</tbody>
</table>
For subjective uncertainty scores, the Greenhouse-Geisser correction for departure from Sphericity is considered, as the value of epsilon is under 0.75. The results show that there is a significant effect of the distance gap on subjective uncertainty scores, Wilks’s Lambda = 0.36, $F(8, 504) = 110.25, p < .001$. The following Tukey’s HSD tests reveal that the distance gap of 36 m is significantly different from other distance gaps except for 32 m and 40 m (see Table 3.2).

Table 3.2: Tukey’s HSD test of a repeated-measures one-way ANOVA of subjective uncertainty scores (**** 0.001, ** 0.01, * 0.05, . 0.1, ′ 1; LCL= Lower Control Limit for the mean; UCL= Upper Control Limit for the mean), first published in [175].

<table>
<thead>
<tr>
<th>Gap pair</th>
<th>Difference</th>
<th>LCL</th>
<th>UCL</th>
<th>P-value (Sig.)</th>
</tr>
</thead>
<tbody>
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<td>-0.148</td>
<td>-0.349</td>
<td>0.052</td>
<td>0.346</td>
</tr>
<tr>
<td>28-20</td>
<td>-0.365</td>
<td>-0.566</td>
<td>-0.164</td>
<td>0.000***</td>
</tr>
<tr>
<td>32-20</td>
<td>-0.697</td>
<td>-0.898</td>
<td>-0.496</td>
<td>0.000***</td>
</tr>
<tr>
<td>36-20</td>
<td>-0.863</td>
<td>-1.064</td>
<td>-0.662</td>
<td>0.000***</td>
</tr>
<tr>
<td>40-20</td>
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<td>-0.929</td>
<td>-0.528</td>
<td>0.000***</td>
</tr>
<tr>
<td>44-20</td>
<td>-0.408</td>
<td>-0.609</td>
<td>-0.207</td>
<td>0.000***</td>
</tr>
<tr>
<td>48-20</td>
<td>-0.094</td>
<td>-0.295</td>
<td>0.107</td>
<td>0.879</td>
</tr>
<tr>
<td>52-20</td>
<td>0.301</td>
<td>0.100</td>
<td>0.502</td>
<td>0.000***</td>
</tr>
<tr>
<td>28-24</td>
<td>-0.217</td>
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<td>0.023.</td>
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<tr>
<td>32-24</td>
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<td>-0.750</td>
<td>-0.348</td>
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</tr>
<tr>
<td>36-24</td>
<td>-0.715</td>
<td>-0.916</td>
<td>-0.514</td>
<td>0.000***</td>
</tr>
<tr>
<td>40-24</td>
<td>-0.580</td>
<td>-0.781</td>
<td>-0.379</td>
<td>0.000***</td>
</tr>
<tr>
<td>44-24</td>
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<td>-0.059</td>
<td>0.002*</td>
</tr>
<tr>
<td>48-24</td>
<td>0.055</td>
<td>-0.146</td>
<td>0.256</td>
<td>0.995</td>
</tr>
<tr>
<td>52-24</td>
<td>0.449</td>
<td>0.248</td>
<td>0.650</td>
<td>0.000***</td>
</tr>
<tr>
<td>32-28</td>
<td>-0.332</td>
<td>-0.533</td>
<td>-0.131</td>
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</tr>
<tr>
<td>36-28</td>
<td>-0.498</td>
<td>-0.699</td>
<td>-0.297</td>
<td>0.000***</td>
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<tr>
<td>40-28</td>
<td>-0.363</td>
<td>-0.564</td>
<td>-0.162</td>
<td>0.000***</td>
</tr>
<tr>
<td>44-28</td>
<td>-0.043</td>
<td>-0.244</td>
<td>0.158</td>
<td>0.999</td>
</tr>
<tr>
<td>48-28</td>
<td>0.271</td>
<td>0.071</td>
<td>0.472</td>
<td>0.001**</td>
</tr>
<tr>
<td>52-28</td>
<td>0.666</td>
<td>0.465</td>
<td>0.867</td>
<td>0.000***</td>
</tr>
<tr>
<td>36-32</td>
<td>-0.166</td>
<td>-0.367</td>
<td>0.035</td>
<td>0.202</td>
</tr>
<tr>
<td>40-32</td>
<td>-0.031</td>
<td>-0.232</td>
<td>0.170</td>
<td>1.000</td>
</tr>
<tr>
<td>44-32</td>
<td>0.289</td>
<td>0.088</td>
<td>0.490</td>
<td>0.000***</td>
</tr>
<tr>
<td>48-32</td>
<td>0.604</td>
<td>0.403</td>
<td>0.804</td>
<td>0.000***</td>
</tr>
<tr>
<td>52-32</td>
<td>0.998</td>
<td>0.797</td>
<td>1.199</td>
<td>0.000***</td>
</tr>
<tr>
<td>40-36</td>
<td>0.135</td>
<td>-0.066</td>
<td>0.336</td>
<td>0.486</td>
</tr>
<tr>
<td>44-36</td>
<td>0.455</td>
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<td>0.000***</td>
</tr>
<tr>
<td>48-36</td>
<td>0.770</td>
<td>0.569</td>
<td>0.970</td>
<td>0.000***</td>
</tr>
<tr>
<td>52-36</td>
<td>1.164</td>
<td>0.963</td>
<td>1.365</td>
<td>0.000***</td>
</tr>
<tr>
<td>44-40</td>
<td>0.320</td>
<td>0.119</td>
<td>0.521</td>
<td>0.000***</td>
</tr>
<tr>
<td>48-40</td>
<td>0.635</td>
<td>0.434</td>
<td>0.836</td>
<td>0.000***</td>
</tr>
</tbody>
</table>
### 3 Investigating Driver Uncertainty in Lane Change Maneuvers

<table>
<thead>
<tr>
<th>Gap pair</th>
<th>Difference</th>
<th>LCL</th>
<th>UCL</th>
<th>P-value (Sig.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>52-40</td>
<td>1.029</td>
<td>0.828</td>
<td>1.230</td>
<td>0.000***</td>
</tr>
<tr>
<td>48-44</td>
<td>0.314</td>
<td>0.114</td>
<td>0.515</td>
<td>0.000***</td>
</tr>
<tr>
<td>52-44</td>
<td>0.709</td>
<td>0.508</td>
<td>0.910</td>
<td>0.000***</td>
</tr>
<tr>
<td>52-48</td>
<td>0.395</td>
<td>0.194</td>
<td>0.595</td>
<td>0.000***</td>
</tr>
</tbody>
</table>

Action proportion is the proportion of the action of either the steering or braking actions at each distance gap. A histogram with the action proportion for the braking action and steering action is shown in Figure 3.5. As the distance gap increases, the action proportion for braking gradually declines while the action proportion for steering raises. The braking action is preferred by 80 percent of participants at small distance gaps (< 32 m), while the steering action is preferred at large distance gaps (> 44 m). The transition of the preferred action from braking to steering occurs at the middle distance gaps of 36 m and 40 m, where subjects have the highest subjective uncertainty scores and longest reaction times (see Figure 3.5).

![Figure 3.5: Action proportion at different distance gaps in the first experiment, first published in [175].](image)

### 3.4.6 Summary

Summarizing the results above, at small (≤ 32 m) or large distance gaps (≥ 44 m) between the subject vehicle and the approaching target vehicle, participants are certain with quick reactions and low uncertainty scores in lane change maneuvers [175]. The braking action is preferred at small distance gaps (≤ 32 m) and the steering action is preferred at large distance gaps (≥ 44 m) [175].
middle distance gaps of 36 m and 40 m, participants are very uncertain with relatively long reaction times and high uncertainty scores, as well as no obvious difference regarding action proportion [175]. Moreover, the distance gap of 36 m is representative with its maximum reaction time and maximum uncertainty score. The measure of driver uncertainty can help decide the range of areas where drivers are uncertain and later contribute to the development of MBLCDAS considering driver uncertainty.

Some participants criticized that the acoustic signal which informed them when to look at the left side mirror was not intuitive and they usually began their observation earlier instead of waiting for the acoustic signal in a real traffic scenario [175]. For this, they were explained in the experiment that the setting of the acoustic signal could be imagined as some events that happened in front, which were used to trigger the lane change maneuvers [175].

However, only the distance gap between the subject vehicle and the approaching vehicle is varied in this study, while the closing speed is kept constant [175]. In order to draw a general conclusion about driver uncertainty, the speed difference between the subject vehicle and approaching vehicle needs also to be considered [175]. The next step is a follow-up study, which aims to overcome the limitation of a fixed closing speed and investigate whether the closing speed and the combination of the distance gap and the closing speed, namely TTC also influence driver uncertainty during decision-making in lane change maneuvers.

3.5 Study II: Investigating the Influence of Time to Collision (TTC) and Closing Speed on Driver Uncertainty

As a follow-up study, the second experiment mainly investigates driver uncertainty under influences of TTC and closing speed between the subject vehicle and an approaching target vehicle in lane change maneuvers, in order to answer the RQ 1b.

3.5.1 Participants

29 students (17 males and 12 females; age M = 24.2 years, SD = 3.4) recruited from the student pool of Carl von Ossietzky University of Oldenburg voluntarily took part in the second experiment in the driving simulator [172]. They all had a valid German drivers license with an average of 6.5 years of driving experience (SD = 3.1). In the end, they were paid 15 Euro for 1.5-hour participation.

3.5.2 Apparatus and Driving Scenario

The study was conducted in a fixed based driving simulator with a 160-degree beamer projection in the OFFIS-Institute for Information Technology. Traffic scenarios and simulations were simulated
using SILAB software. Additionally, a keypad was installed beside the steering wheel on the right (see Figure 3.6).

![Image of driver view through windshield and left side mirror at the beginning of the second experiment in the driving simulator. The keypad is put next to the steering wheel (in the lower-right corner).]

Figure 3.6: Driver view through windshield and left side mirror at the beginning of the second experiment in the driving simulator. The keypad is put next to the steering wheel (in the lower-right corner).

The subject vehicle (A) was controlled by an Adaptive Cruise Control (ACC) plus Lane Keeping Assistance (LKAS), which meant that participants did not need to drive by themselves [175]. At the beginning, the subject vehicle in the right lane accelerated until 130 km/h [172]. Then a slower vehicle (B) (100 km/h) was placed 100 m in front of the subject vehicle (A), while a faster rear vehicle (C) (at the speed of 140 km/h, 145 km/h, or 150 km/h) approached (see Figure 3.7) [172].

![Image of simulated lane change scenario used in the second experiment: The subject vehicle (A) driving at 130 km/h approaches a slower lead vehicle (B) driving at 100 km/h, while a faster rear target vehicle (C) (at the speed 140 km/h, 145 km/h, or 150 km/h) approaches the subject vehicle (A).]

Figure 3.7: The simulated lane change scenario used in the second experiment: The subject vehicle (A) driving at 130 km/h approaches a slower lead vehicle (B) driving at 100 km/h, while a faster rear target vehicle (C) (at the speed 140 km/h, 145 km/h, or 150 km/h) approaches the subject vehicle (A).
3.5.3 Experiment Design

As independent variables, TTC and closing speed (Figure 3.7) are chosen and manipulated in this experiment. As dependent variables, reaction times, uncertainty scores, and action proportion for lane change decisions are recorded. Reaction time is defined as the time interval between the acoustic signal and driver’s response actions (steering or braking) for lane change decisions [172]. Uncertainty scores is typed by participants after giving response actions, with the respective number of 1 (very uncertain) to 5 (very certain) on the keypad (see Figure 3.5) [172]. Regarding action proportion for lane change decisions, steering represents the decision of changing the lane, while braking means no lane change decisions.

To explore appropriate ranges of TTC and closing speed that trigger different drivers’ uncertainty states for this study, the experimental conditions used in the previous experiment [175] have been considered. In the previous study (section 3.4), the result shows that the distance gap has a significant impact on driver uncertainty [175]. Hence, the range of the distance gap from 20 m to 52 m with 4 m interval chosen in the first study is considered as a reference for the current experiment. As distance gap and TTC are functionally dependent, the corresponding TTC could be calculated within the range of 7.19 seconds up to 18.71 seconds (7.19 s, 8.63 s, 10.07 s, 11.51 s, 12.95 s, 14.39 s, 15.83 s, 17.27 s, and 18.71 s) in 9 steps for this study [172].

In addition to the distance gap, closing speed between the subject vehicle and the approaching target vehicle used in the previous study has also been taken into account for this study. In the first experiment [175], the closing speed of 2.78 m/s (10 km/h) is considered with reference to the advisory speed limit on German motorways. In order to cover the lane change situations where the approaching vehicle drives much faster on motorways, high closing speeds of 4.17 m/s (15 km/h) and 5.56 m/s (20 km/h) are also considered for this study. Based on the selected TTCs and closing speeds, distance gaps for each closing speed can be calculated. All 27 combinations of a 3 closing speeds x 9 TTCs are shown in Table 3.3.

<table>
<thead>
<tr>
<th>CS (m/s)</th>
<th>Distance Gap (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.78</td>
<td>20 24 28 32 36 40 44 48 52</td>
</tr>
<tr>
<td>4.17</td>
<td>30 36 42 48 54 60 66 72 78</td>
</tr>
<tr>
<td>5.56</td>
<td>40 48 56 64 72 80 88 96 104</td>
</tr>
</tbody>
</table>

Table 3.3: An overview of 27 combinations of TTC and closing speed (CS), first published in [172].

A within-subject design was used in the study. To each participant, three blocks were presented
and there was a 2-minute break between blocks. In each block, 27 combinations were presented 5 times, which resulted in 135 trials per subject. Each trial took about 10 seconds [172]. The order of combinations was randomly assigned in each block. The whole experiment including instructions and training lasted about 90 minutes.

### 3.5.4 Procedure

First, participants signed an informed consent and completed a demographic survey to collect their information about age, gender, and driving experience [172]. Additionally, participants read a handout with the procedure and safety instructions [172]. After that, they familiarized themselves with the driving simulator environment. Before the experiment began, they were asked to put their hands on the steering wheel and their right feet on the brake pedal, to give lane change decisions through response actions of either steering or braking.

At the start of the experiment, they followed the lead vehicle (B). After 4.5 seconds, an acoustic signal was given and a rear vehicle (C) was set up with various combinations of distance gap and closing speed [172]. After hearing the acoustic signal, subjects were instructed to look at the left mirror and estimate the possibility of doing a lane change in different situations: When it was possible to change the lane, they were asked to steer left about 45 degrees to show their decisions for changing the lane; when it was not possible to change the lane, they were asked to brake to show their no lane change decisions [172]. After each response action, subjects were asked to give their uncertainty score on a 5-point Likert scale (1 for "very uncertain", 5 for "very certain") on the keypad [172]. Regarding entering an uncertainty score, participants were instructed that rating was not about the correctness of their decisions or the speed of the approaching car, but the overall difficulty they felt in making lane change decisions [175]. After typing an uncertainty score and confirming with the key “Enter” on the keypad, the next trial began.

### 3.5.5 Results

The data in CSV format collected from simulator platform was analyzed in RStudio software (Version 0.98.1028). According to Triggs and Harris [148], driver reaction time is longer in difficult visual or cognitive conditions than easy conditions. In this study, it is assumed that when drivers are uncertain, they usually have difficulty in making lane change decisions, which may cause long reaction times with low subjective uncertainty scores and random response actions. Besides, the negative correlation between subjective uncertainty score and reaction time is also expected. The results will be reported as follows: reaction times, subjective uncertainty scores, the correlation between reaction times and uncertainty scores, action proportion for lane change decisions.

**Reaction Times** Figure 3.8 shows mean reaction times of 3 closing speeds at 9 TTCs. It is illustrated that for each closing speed, mean reaction time increases up to a certain point and then begins to drop with the increasing TTC. In addition, with the increasing closing speed, the mean reaction time with its maximum appears earlier.
Namely, the faster the approaching vehicle drives, the earlier driver uncertainty appears with long reaction time. Because of the nonlinear relation between independent variables (TTC and closing speed) and a dependent variable (reaction time), multiple polynomial regression is considered. The best fit of the model to predict reaction time from TTC and closing speed is looked for among different degrees of nonlinear models. Using the “poly” function in RStudio, multiple polynomial regressions were conducted from the degree of 1 to 5. Analysis of variance test shows that the fourth order polynomial is the best fit of model ($R^2 = .13, F(11, 11164) = 162.6, p < .001$), indicating that both TTC and closing speed have significant effects on reaction time. Furthermore, Friedman’s test ($\chi^2(2) = 46.6, p < .001$) shows that mean reaction time with its maximum value appears earlier with the increasing closing speed. In other words, the faster the approaching vehicle drives, the earlier participants become uncertain with longer responses.

**Uncertainty Scores** Figure 3.9 shows mean uncertainty scores of 3 closing speeds at 9 TTCs. In opposition to Figure 3.8, it can be seen that for each closing speed, mean uncertainty score initially increases to a certain maximum and then begins to drop down with the increasing TTC. In addition, mean uncertainty score with its maximum value for each closing speed appears earlier with the increasing closing speed.
In other words, the faster the approaching vehicle drives, the earlier participants become uncertain with higher ratings of driver uncertainty. Based on the Figure 3.9 and the ordinal data type of uncertainty score, ordinal regression was conducted with the “polr” function which is part of “MASS” package in RStudio to predict uncertainty scores from TTC and closing speed.

Based on the estimated log-odds coefficients, odds ratio coefficients and p-values are calculated separately and summarized in Table 3.4. In the ordinal regression model, as the first value of factor variables (TTC= 7.19 s and closing speed = 2.78 m/s) are treated as the baseline, no outputs for these two variables are given in Table 3.4. The null hypothesis of the ordinal regression model is that individual predictor’s regression coefficient is zero. As all predictors have significant p-values ($p < .001$) in the test statistics, the null hypothesis can be rejected. In other words, both TTC and closing speed significantly influence driver uncertainty and need to be included in the ordinal regression model.
Table 3.4: Outputs of ordinal regression analysis (cs: closing speed).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Log-odds</th>
<th>Odds ratio</th>
<th>Std. Error</th>
<th>t value</th>
<th>p value</th>
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</tr>
<tr>
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<tr>
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<tr>
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<td>0.077</td>
<td>-11.741</td>
<td>0.000</td>
</tr>
<tr>
<td>ttc18.71</td>
<td>-0.542</td>
<td>0.582</td>
<td>0.078</td>
<td>-6.989</td>
<td>0.000</td>
</tr>
<tr>
<td>cs4.17</td>
<td>-0.151</td>
<td>0.860</td>
<td>0.042</td>
<td>-3.619</td>
<td>0.000</td>
</tr>
<tr>
<td>cs5.56</td>
<td>0.162</td>
<td>1.176</td>
<td>0.042</td>
<td>3.824</td>
<td>0.000</td>
</tr>
</tbody>
</table>

The most important items are regression coefficients, which are values of the column “Odds ratio” in Table 3.4. The highest odds ratio is 1.176 of the variable “cs5.56”, which means that when the value of closing speed at 5.56 m/s increases from 0 to 1, the likelihood that participants rate their uncertainty as “5” is 1.176 times greater than participants rate it as “4”, “3”, “2” or “1”. It means that the closing speed of 5.56 m/s has more influences on subjective uncertainty scores than other variables. In addition, Friedman’s test ($\chi^2(2) = 54.2, p < .001$) indicates that mean uncertainty score with its maximum value appears earlier with the increasing closing speed. In other words, it demonstrates that the faster an approaching vehicle drives, the earlier participants become uncertain with high uncertainty scores.

**The Correlation between Reaction Time and Uncertainty Score** In order to test the correlation between a continuous variable (reaction time) and an ordinal variable (uncertainty score), both polyserial correlation and Spearman rank correlation are considered. The polyserial correlation is used under the assumption that the variable of uncertainty score is normally distributed. In RStudio, polyserial correlation was conducted using maximum-likelihood estimator with the function “polyserial” in “polycor” package. The test of bivariate normality shows that the assumption of polyserial correlation is violated ($\chi^2(14) = 1310, p < .001$). Therefore, Spearman rank correlation is finally chosen for the correlation test. Using the “cor.test” function with the “spearman” method in RStudio, $\rho = -0.4, p < .001$, which indicates that the negative correlation between reaction time and uncertainty score is significant.

**Action Proportion for Lane Change Decisions** In the experiment, lane change decisions are indicated by either the steering action for the decision of changing the lane, or the braking action for the decision of no lane changes. The action proportions of lane change decisions for all closing speeds are shown in Figure 3.10 ~ 3.12. For the closing speed of 2.78 m/s, no lane change decisions are preferred when the TTC is shorter than 17.27 s (distance gap = 48 m). At the turning point (the transition of the majority of decisions from no lane changes to lane changes) of 18.71 s (distance gap = 52 m), the distributions of the action proportion become similar, where mean reaction time becomes longest of 1.70 s with reference to Figure 3.8.
3 Investigating Driver Uncertainty in Lane Change Maneuvers

For the closing speed of 4.17 m/s, no lane change decisions are chosen when the TTC is shorter than 12.95 s (distance gap = 54 m). At the turning point of 14.39 s (distance gap = 60 m), the distributions of the action proportion also become similar, where the mean reaction time becomes longest of 1.74 s with reference to the Figure 3.8.

For the closing speed of 5.56 m/s, no lane change decisions are preferred when the TTC is shorter than 10.07 s (distance gap = 56 m). At the turning point of 11.51 s (distance gap = 64 m), the distributions of the action proportion become similar, where mean reaction time becomes longest of 1.63 s with reference to the Figure 3.8.
It can be concluded that with the increasing closing speed from 2.78 m/s to 4.17 m/s, 5.56 m/s, the turning point (the transition of the majority of decisions from no lane changes to lane changes) moves towards short TTCs separately from 18.71 s to 14.39 s, 11.51 s. A repeated measure logistic regression analysis was conducted to predict drivers’ lane change decisions using TTC and closing speed as predictors. A test of the full model (with the consideration of TTC and closing speed) against a constant model (without the consideration of TTC and closing speed) is statistically significant, indicating that TTC and closing speed as a set reliably distinguish lane change decisions from no lane change decisions ($\chi^2(3) = 8247.6, p < .001$). Nagelkerke’s $R^2$ of .687 indicates a moderately strong relation between lane change decisions and two predictors. Friedman’s test ($\chi^2(2) = 36.7, p < .001$) shows that with the increasing closing speed, the turning point from lane change decisions to no lane change decisions appears earlier with short TTCs. In other words, as an approaching vehicle drives faster, participants’ decisions for changing the lane begin earlier.

### 3.5.6 Summary

**Results** Both TTC and closing speed have a significant effect on reaction times, uncertainty scores and action proportion for lane change decisions. As the closing speed of the approaching vehicle increases, long reaction times, high uncertainty scores or decisions for changing a lane appears earlier with short TTCs. Compared with the first experiment [175], this study has additionally demonstrated that closing speed and TTC have significantly influenced driver uncertainty in lane change maneuvers. As TTC increases while keeping the closing speed of an approaching car constant, driver uncertainty reflected by reaction times and subjective uncertainty scores form (opposite) U curves (see Figures 3.8 and 3.9). The faster the approaching car drives, the earlier driver uncertainty appears with long reaction times or high rating of subjective uncertainty. The negative correlation between reaction time and uncertainty score implies that reaction time can be considered as an indirect indicator to describe driver uncertainty during decision-making in lane change maneuvers.
In Figures 3.8 and 3.9, it is illustrated that curves of three closing speeds are similar, even if curves of closing speed of 2.78 m/s and 4.17 m/s are not complete due to the insufficient data. It could be inferred that with increasing closing speed (faster than 5.56 m/s), the curves of both reaction times and subjective uncertainty scores reflecting driver uncertainty will still have the same patterns as in Figures 3.8 and 3.9.

Regarding action proportions for lane change decisions, it can be found that at the turning point (the transition of the majority of decisions from no lane changes to lane changes), distributions of action proportions of both decisions become similar but with longest reaction times. The reason could probably be that when drivers become uncertain, they will observe the situations more often to compare the alternatives, which leads to long reaction times [119]. In the end, they still have no ideas about which actions should be taken and may execute actions randomly.

Because of the functional relation between TTC and distance gap, it can be inferred that with the change of closing speed, the range of distance gaps also changes, and drivers are uncertain at medium distance gaps and certain at small or large distance gaps, which is consistent with the results in the first study [175].

**Limitations**

In this study, the investigation of driver uncertainty in lane change maneuvers considers only TTC and closing speed. Other factors like driver age or type need also to be considered in future investigations. In addition, although the experiment was well controlled in the driving simulator, it is unclear that the results are also valid in the field.

In the experiment, subjective uncertainty scores that are used to measure driver uncertainty were collected only once after each lane change situation. However, it is unclear how uncertainty actually develops in the whole lane change situation and how it can be measured continuously in appropriate time slots. Besides, the accuracy of measurements of driver uncertainty using reaction times and subjective uncertainty scores may be questionable. Physiological measurements such as fNIRS (functional near-infrared spectroscopy) and fMRI (functional magnetic resonance imaging) can be considered to help to measure and identify driver uncertainty in the future studies.
4 Developing a Model-Based Lane Change Decision Aid System

Based on the data collected from the empirical experiment in the last chapter, chapter 4 presents the development of a model of driver uncertainty inferring drivers’ uncertainty states and further a Model-Based Lane Change Decision Aid System (MBLCDAS) that adapts to driver uncertainty, which refers to the Step 2 and Step 3 in the research approach. This chapter consists of 6 sections: In section 4.1, the concept and structure of the proposed MBLCDAS are introduced; as an important component of the proposed MBLCDAS, the development of the probabilistic model of driver uncertainty is described in section 4.2; in sections 4.3 and 4.4, the decision recommendation and the Human Machine Interface of the proposed MBLCDAS are presented; in section 4.5, the implementation of the proposed MBLCDAS is introduced, followed by a summary of the chapter (section 4.6).

4.1 Concept and Structure of A Model-Based Lane Change Decision Aid System

The concept of the proposed Model-Based Lane Change Decision Aid System (MBLCDAS) is that it considers both criticality and driver uncertainty in lane change maneuvers, and especially it can recognize when drivers are uncertain or certain during decision-making and adapt its information behavior to the drivers’ uncertainty states with corresponding decision recommendations [171]. The criticality refers to the traffic safety when executing a lane change maneuver and is classified into two states: “safe” and “unsafe”. Based on the concept of the proposed MBLCDAS, drivers’ uncertainty states are divided into “certain” and “uncertain”. The adaptive assistance of the proposed MBLCDAS can be shown in its information behavior: A non-obtrusive aid will be given when drivers are certain in the decision-making processes, according to the definition of adaptive automation that assistance should be given when needed; a helpful aid will be provided timely when drivers are uncertain about lane change decisions considering the research hypothesis building driver trust by taking driver uncertainty into account. The functionality of the proposed MBLCDAS is described as follows [172, 171]:

- If it is safe to change a lane and drivers are certain, the proposed MBLCDAS will suggest to change the lane in an unobtrusive way, in order not to disturb drivers and let them decide by themselves.
4 Developing a Model-Based Lane Change Decision Aid System

- If it is safe to change a lane and drivers are uncertain, the proposed MBLCDAS will suggest to change the lane in an active way, to reduce driver uncertainty on time and help draw lane change decisions.

- If it is unsafe to change a lane in the given situation, the proposed MBLCDAS will suggest not to change the lane actively, regardless of drivers’ uncertainty states, as the priority of the criticality is higher than drivers’ uncertainty states.

Concerning the structure of the proposed MBLCDAS, a schematic overview [173] of the proposed system is shown in Figure 4.1.

![Figure 4.1: A schematic overview of the proposed MBLCDAS.](image)

Depending on the traffic information of lane change situations (“Traffic Situation”), on the one hand, a probabilistic model of driver uncertainty (“Model of Driver Uncertainty”) is developed. The concept of this probabilistic model is that it can infer the driver’s uncertainty state as either “uncertain” or “certain” during decision-making in lane change maneuvers, depending on the variables that have potential impacts on driver uncertainty [172]. A binary random variable $U$ with the possible values \( \text{Val}(U) = \{ \text{uncertain}, \text{certain} \} \) is defined to represent the driver’s uncertainty state and $U$ is called the class variable that is to be inferred [172]. A set of attributes that describe traffic situations is needed to predict $U$, which is denoted by $X$. For a given traffic situation encoded by $X = x$, a probabilistic model inferring conditional probabilities of driver uncertainty can be developed, which can be written as $P(U|X = x)$. Then a decision threshold $t_d$ is used to classify the driver’s uncertainty state as “uncertain”, if $P(U = \text{certain}|X = x) \leq t_d$ and “certain” otherwise. The model of driver uncertainty can be utilized to develop MBLCDAS, i.e., it is able to classify the driver’s uncertainty states in a given lane change situation based on the traffic information derived from the vehicle sensors. The classified driver’s uncertainty state can further contribute to the interface design (“Human Machine Interface”) of the proposed MBLCDAS.

On the other hand, recommendations for lane change decisions (“Decision Recommendation”) can be classified from the experimental data in the driving simulator study (chapter 3), to provide traffic safety for lane change maneuvers. An action threshold $t_a$ is needed to help suggest whether to change the lane by steering or not by braking in a given lane change situation [171]. According to the traffic information (i.m., distance gap denoted as $d_{gap}$) and drivers’ preferences for lane change
decisions, the given lane change situation can be classified as either “safe” if \( d_{gap} \geq t_a \) or “unsafe” otherwise. For a “safe” lane change situation, a decision to change the lane will be recommended by the proposed MBLCDAS, while a decision to stop will be suggested for an “unsafe” lane change situation. The decision recommendation can also trigger the corresponding information on the HMI (“Human Machine Interface”). As the proposed MBLCDAS considers both criticality and driver uncertainty, the information displayed on the interface should be able to reflect driver uncertainty and also the current traffic criticality.

4.2 Developing a Probabilistic Model of Driver Uncertainty

The proposed MBLCDAS is supposed to recognize drivers’ uncertainty states in various lane change situations. The precondition for the proposed MBLCDAS is a model of driver uncertainty [172]. The Bayesian network is chosen to infer drivers’ uncertainty states during decision-making in lane change maneuvers (see section 2.5.2). To develop a probabilistic model of driver uncertainty, first data needs to be collected (section 4.2.1) and relevant attributes need to be selected as inputs of the model (section 4.2.2). A mapping from the subjective uncertainty scores to the conceptualized drivers’ uncertainty states is introduced in section 4.2.3. After having the attributes and the variable for the model, three candidate models are introduced (section 4.2.4). After parameters and the structure learning (section 4.2.5), a model is selected among the candidate models (section 4.2.6) and then evaluated (section 4.2.7). In section 4.2.8, the performance of the model is described. In the end (section 4.2.9), the classification of the outputs of the model to the two uncertainty states as either “certain” or “uncertain” is presented.

4.2.1 Data Collection

As reported in chapter 3, an experiment has been conducted with 29 participants to study driver uncertainty under the influence of distance gap, TTC, and closing speed between the subject vehicle and the approaching target vehicle.

In total, 11653 trials were collected from the second experiment to form the basis for developing the model of driver uncertainty during decision-making in lane change situations [172]. A single sample was recorded for each trial. In each trial, an acoustic signal was given to trigger the lane change maneuver. The condition in which the information was measured when the acoustic signal was given, was called start condition. After the acoustic signal was provided, the situations still further developed until participants made their lane change decisions with either braking or steering actions. The condition where the information was measured when participants’ actions were executed, was defined as reaction condition.

In ISO 17387, time to collision is “estimated time that it would take a target vehicle to collide with the subject vehicle if the subject vehicle were in the target vehicle’s path and the target vehicle’s current closing speed remained constant “ [70, p. 4]. According to this, TTC can be calculated by
distance gap and closing speed. In the start condition, information of closing speed, distance gap, and TTC between the approaching vehicle and the subject vehicle was collected for each sample. In the reaction condition, the closing speed, distance gap and TTC between the subject vehicle and the approaching vehicle/lead vehicle were also calculated in post-processing, due to the non-interactive nature of the experiment. In the experiment, the reaction time is the time measured between the acoustic signal and actions. However, executing the action (braking or steering actions) alone also takes some time, which needs to be excluded from the reaction times. With this consideration, the measured reaction times from the experiment need to be adjusted. Reviewing the literature regarding the foot movement times and steering wheel response times, the normal foot responses take an average reaction time of 500 ms and the hand control takes an average reaction time of 370 ms [122]. Based on this, 500 ms is excluded from the measured reaction time for each sample.

After participants’ reactions, reaction time measured from the acoustic signal to participants’ actions, typed subjective uncertainty scores, and lane change decisions indicated by actions were recorded for each sample [172]. Additionally, participants’ demographic information such as driver age, gender, and driving experience has also been collected at the beginning of the experiment in the demographic questionnaire [172].

4.2.2 Attribute Selection

As three variables (distance gap, closing speed and TTC) are functionally dependent, only two of them are needed for selecting the attributes for the model. It means that two of these three variables are sufficient and a third one does not provide any additional information. In order to select two attributes that are supposed to have a greater individual influence on driver uncertainty than a third one, Mutual Information (MI) is taken into account. MI is a measure of the amount of information that one random variable has about another variable, which can quantify the relevance of a feature subset for the feature selection [152]. The mutual information between two discrete random variables $X, Y$ jointly distributed according to $p(x, y)$ is given by:

$$ I(X; Y) = \sum_{x,y} p(x, y) \log \frac{p(x, y)}{p(x)p(y)} \quad (4.1) $$

After calculating the MI between the uncertainty scores and three variables separately with the “infotheo” package in R Studio (Version 1.0.143), the variables of distance gap (MI= 0.12) and TTC (MI= 0.04) with higher MI scores were chosen as attributes for the model of driver uncertainty.

In the experiment, lane change situations between the subject vehicle and the approaching target vehicle were manipulated to trigger driver uncertainty. The situations between the subject vehicle and the lead vehicle were not manipulated, as the driver uncertainty associated with the lead vehicle mainly induced by the braking of the lead vehicle has been already investigated [156]. As at the time of decision-making in lane change maneuvers (reaction condition), the situation between the subject vehicle and the approaching target vehicle varied from the situation in the start condition, along with the change of the situation between the subject vehicle and the lead vehicle. Hence, regarding the attributes of the model, the situations between the subject vehicle and the lead vehicle are also
4 Developing a Model-Based Lane Change Decision Aid System

taken into account. With the considerations above, four attributes with discretized ten intervals (see Figure 4.6) in reaction condition are defined for the model of driver uncertainty and illustrated in Figure 4.2:

- $TTC_A$: The time to collision between the subject vehicle and the lead vehicle in the same lane at the moment of making lane change decisions [172].
- $G_A$: The distance gap between the subject vehicle and the lead vehicle in the same lane at the moment of making lane change decisions [172].
- $TTC_B$: The time to collision between the subject vehicle in the right lane and the approaching vehicle in the left lane at the moment of making lane change decisions [172].
- $G_B$: The distance gap between the subject vehicle in the right lane and the approaching vehicle in the left lane at the moment of making lane change decisions [172].

![Figure 4.2: The illustration of four attributes for the model of driver uncertainty in a simulated lane change scenario: The subject vehicle (A) approaches a slower lead vehicle (B), while a faster target vehicle (C) approaches in the left lane.](image)

### 4.2.3 Mapping of Driver Uncertainty

According to the concept of the model, the output of the model should be a binary uncertainty state of either “certain” or “uncertain”. However, the collected subjective uncertainty scores in the driving simulator experiment had five levels (from 1 = very uncertain to 5 = very certain). Therefore, a mapping of uncertainty scores (1-5) rated by participants onto the conceptualized two uncertainty states of the model is needed [172].

With the x-axis of distance gap and a y-axis of closing speed, density plots for all uncertainty scores are shown in Figure 4.3. The frequency of the points is displayed by the color changing from blue to red: the redder the points are, the more frequently the points appear [172]. In the Hexbin scatter plot for the uncertainty scores of 1-3, it is found that the distributions of these three plots are very similar: Most points with the red color representing low uncertainty scores appear at the middle distance gaps, which is consistent with the experimental result that drivers are uncertain at middle distance gaps. As the uncertainty scores of 1 to 3 are relatively low scores representing that drivers are relatively “very uncertain”, the uncertainty scores of 1 to 3 seem to be a good candidate for a

---

1The decision of ten intervals of the attributes is based on the 9 levels of the attributes and also the suggested discretizations of the Netica software according to the given data set.
mapping to the “uncertain” state. Conversely, the Hexbin scatter plot of the uncertainty score of 5 shows an opposite distribution of frequencies: Most points with the red color appear at small or large distance gaps, which is also consistent with the experimental result that drivers are certain at small or large distance gaps. As the uncertainty score of 5 is a high score representing that drivers are “very certain” in the given lane change situation, it can be assigned to another cluster classified as “certain”. The Hexbin scatter plot for the uncertainty score of 4 shows an equally distributed frequency with the characters of both patterns.

Based on the Hexbin scatter plot, it is assumed that there could be two clusters of uncertainty states. In order to statistically examine whether this visual hypothesis is valid, Kullback-Leibler Divergence (KLD) is used. KLD is a measure to compare the difference between two probability distributions [80]. It is an information-based measure of disparity among probability distributions [92] and a widely used tool in pattern recognition [34]. For distributions \( P \) and \( Q \) of a discrete random variable, the Kullback–Leibler divergence from \( Q \) to \( P \) is defined [93] as \( D_{KL} (P || Q) \) and is calculated as follows:

\[
D_{KL} (P \| Q) = \sum_i P(i) \log \frac{P_i}{Q_i}
\]  

The Kullback–Leibler divergence is non-negative, which means that \( D_{KL} (P \| Q) \geq 0 \). A Kullback–Leibler divergence of 0 indicates that two distributions are same. The higher the Kullback–Leibler divergence is, the more different the two distributions are.

Figure 4.3: The Hexbin scatter plot for all the uncertainty scores (uncertainty= 1, 2, 3, 4, 5).
The KLD\textsuperscript{2} was calculated for each uncertainty score from 1 to 5 with the \textit{KL.plugin} function in RStudio and the summary of KLDs is shown in Table 4.1. For the uncertainty score of 1, its distribution is similar to the uncertainty score of 2, 3, 4 with low KLD scores (\textit{KLD} < 0.5) and different from the uncertainty score of 5 with highest KLD (\textit{KLD} > 1). For the uncertainty score of 2, the KLD is low with the uncertainty score of 1, 3, 4 (\textit{KLD} < 0.5) and highest with the uncertainty score of 5 (\textit{KLD} \approx 1). Similar to the uncertainty score of 1 and 2, the distribution of the uncertainty score of 3 is different from the uncertainty score of 5 with highest KLD (\textit{KLD} > 0.5). The distribution of the uncertainty score of 3 is similar to the uncertainty score of 1, 2, 4 with low KLD (\textit{KLD} < 0.5). For the uncertainty score of 4, its distribution is similar to all other uncertainty scores (1, 2, 3, 5) with low KLD (\textit{KLD} < 0.5). For the uncertainty score of 5, its distribution is different from the uncertainty scores of 1, 2, 3 with high KLD (\textit{KLD} > 0.5) and similar to the uncertainty scores of 4 with low KLD (\textit{KLD} < 0.5). Summarizing these above, two clusters can be derived from the KLD: the uncertainty scores of 1-3 and the uncertainty score of 5, which indicates that the hypothetical two clusters derived from the Hexbin scatter plot are valid. As the distribution of uncertainty score of 4 is similar to both clusters, it can not be assigned to any of these two clusters [172].

Table 4.1: The summary of Kullback-Leibler Divergence for the uncertainty scores of 1, 2, 3, 4 and 5

<table>
<thead>
<tr>
<th>Uncertainty score</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0.165</td>
<td>0.286</td>
<td>0.449</td>
<td>1.053</td>
</tr>
<tr>
<td>2</td>
<td>0.127</td>
<td>0</td>
<td>0.071</td>
<td>0.208</td>
<td>0.928</td>
</tr>
<tr>
<td>3</td>
<td>0.233</td>
<td>0.083</td>
<td>0</td>
<td>0.055</td>
<td>0.608</td>
</tr>
<tr>
<td>4</td>
<td>0.377</td>
<td>0.259</td>
<td>0.060</td>
<td>0</td>
<td>0.334</td>
</tr>
<tr>
<td>5</td>
<td>1.101</td>
<td>1.196</td>
<td>0.696</td>
<td>0.341</td>
<td>0</td>
</tr>
</tbody>
</table>

Because of the similarity of the distributions of the uncertainty scores of 1, 2, 3, they can be treated as a joint group of the uncertainty scores (1-3). A summary of KLD between uncertainty scores (1-3), 4 and 5 are shown in Table 4.2.

Table 4.2: The summary of Kullback-Leibler Divergence for the uncertainty scores of 1-3, 4 and 5.

<table>
<thead>
<tr>
<th>Uncertainty score</th>
<th>1-3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-3</td>
<td>0</td>
<td>0.086</td>
<td>0.711</td>
</tr>
<tr>
<td>4</td>
<td>0.096</td>
<td>0</td>
<td>0.333</td>
</tr>
<tr>
<td>5</td>
<td>0.809</td>
<td>0.341</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 4.2 shows that the KLD between the joint group of uncertainty scores (1-3) and uncertainty

\textsuperscript{2}To cope with the no counts of some uncertainty scores, 1 count was added to the each sample of uncertainty scores.
score of 5 is highest \( KLD \approx 1 \), which indicates a distinct difference between the two clusters and is also in accordance with the Hexbin scatter plots (see Figure 4.4).

![Hexbin scatter plots](image)

Figure 4.4: The Hexbin scatter plots for uncertainty score of 1 to 3 and uncertainty score of 5, first published in [172].

Summarizing the Hexbin scatter plots and Kullback-Leibler Divergence, the uncertainty scores of 1, 2, 3 can be assigned to the “uncertain” state and the uncertainty score of 5 can be mapped to the “certain” state, while the uncertainty score of 4 can be treated as missing values [172]. A database of all 11653 samples is defined as \( D_{all} \). According to this categorization, 7686 samples containing the uncertainty scores of 1,2,3,5 are labeled as “certain” or “uncertain”, while 3967 samples containing the uncertainty score of 4 are unlabeled with missing values.

### 4.2.4 Candidate Models

To model driver uncertainty, the commercial software solution Netica™ Version 5.18 by Norsys, Inc., the most widely used Bayesian network development software, has been considered. With its simple user interface, Netica can create graphical networks. The nodes in Netica are characterized by discrete quantities and Netica is able to make discretization of continuous variables [72]. In Netica, the outputs of models are displayed as bar graphs or a true/false meter for each node [72]. However, Netica’s capabilities of structure learning are limited, which requires to manually select the appropriate model structure for the probabilistic model of driver uncertainty.

Given the evidence of relevant attributes denoted by \( TTC_A, G_A, TTC_B, G_B \), the joint probability distribution of all variables can be written as \( P(U, TTC_A, G_A, TTC_B, G_B) \). The conditional independence of driver uncertainty can be inferred with a Bayesian network: \( P(U|TTC_A, G_A, TTC_B, G_B) \) [172]. The full connected Bayesian network is taken into account using the chain rule that does not introduce any conditional independence assumption between relevant attributes [172]. However, the conditionally non-independent attributes require amounts of estimated parameters to specify the

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4 Developing a Model-Based Lane Change Decision Aid System

probabilities of the model, which makes the model too complex with high variance and possibly cause overfitting [25]. Usually, when the model becomes more complex, the bias will be lower while the variance will be higher [57]. The squared bias describes how much does the average of the estimation differ from the true mean, while variance is the expected squared deviation of a random variable from its mean [57]. On the contrary, the naive Bayesian network is considered as one of the most efficient classifiers [25] that assumes that all available attributes are conditionally independent given the class variable. Due to the strong independence assumption, it reduces the number of estimated parameters and leads to great bias and low variances [104]. However, it is limited to simple models with fixed structure and does not consider the potentially important dependencies between attributes, which leads to the loss of potentially meaningful interactions [94].

As an alternative to fully connected BN and naive BN, a Tree Augmented Naive Bayesian (TAN) classifier with a graph of the tree formed by attributes [131], which was introduced by Friedman et al. [48], is considered. Allowing coding additional statistical dependencies between attributes, TAN classifiers can relax the strong independence assumption of the naive Bayesian network when needed [48]. Particularly, it allows each attribute to depend on a class variable as a parent and at most one other attribute [48]. Then each attribute may only have one parent-variable from the remaining attributes. Hence, a fully connected Bayesian network, a naive Bayesian classifier, and a Tree Augmented Naive Bayesian (TAN) classifier are considered as candidate models [172]. The definitions of them are given as follows:

(1) **Full connected Bayesian network** Let $Y_1, \ldots, Y_n$ denote a set of attributes in an arbitrary sequence, the JPD $P(U, Y_1, \ldots, Y_n)$ can be factorized as [172]:

$$P(U, Y_1, \ldots, Y_n) = P(U) \prod_{i=2}^{n} P(Y_i | Y_{1:i-1}, U) \tag{4.3}$$

(2) **Naive Bayesian network** For a naive Bayesian network, let $Y_1, \ldots, Y_n$ denote a set of attributes in an arbitrary sequence. With the assumption that all attributes are conditionally independent given the parents, the joint probability distribution (JPD) $P(U, Y_1, \ldots, Y_n)$ is factorized as [172]:

$$P(U, Y_1, \ldots, Y_n) = P(U) \prod_{i=1}^{n} P(Y_i | U) \tag{4.4}$$

(3) **Tree Augmented Naive Bayesian network**

Let $A_i$ represent the corresponding parent $Y_j$ of an attribute $Y_i$, the JPD for a TAN classifier can be factorized as follows [172]:

$$P(U, Y_1, \ldots, Y_n) = P(U) \prod_{i=1}^{n} P(Y_i | A_i, U) \tag{4.5}$$

4.2.5 Structure and Parameter Learning

In general, modeling a Bayesian network includes learning the structure and parameters from the data with a variety of learning algorithms [142]. Among the candidate models, the structures of the
fully connected BN and the naive BN are fixed that do not require the structure learning. But the structure of the TAN classifier needs to be learned. Chow [27] proposed a method to efficiently construct a maximum weighted spanning tree which maximized the likelihood that the training data was generated from the tree. This method was then used by Friedman et al. [48] and implemented by Netica for the procedure of learning TAN networks, where the detailed structure for the TAN classifier can be obtained by learning from data. Given the class variable, conditional mutual information measuring the quantity of information shared between each pair of attributes is calculated. Then a maximum weighted spanning tree for these attributes is derived, which results in an undirected tree. By choosing an attribute as a root and setting directions of all edges to be outward from it, the undirected tree can be transformed into a directed one. Examples of the concrete structures for three candidate models are illustrated in Figure 4.5.

![Figure 4.5: Examples of graph-structures of three candidate models (From top to bottom: the naive Bayesian classifier, the TAN classifier, and the fully connected Bayesian network), first published in [172].](image)

About two-thirds (60%) of the database $D_{\text{all}}$ is defined as a training database $D_{\text{Train}}$ containing 7000 randomly selected samples. It includes 4632 labeled training data denoted as $D_{\text{Train}}$, that is used for the model’s structure and parameter learning, and 2368 unlabeled training data denoted
4 Developing a Model-Based Lane Change Decision Aid System

as \( D_{Train_u} \). Regarding the model’s structure and parameter learning, a data set of labeled training data \( D_{Train_l} \) with 4632 samples is trained to learn the structure of TAN classifier, while the complete training data set \( D_{Train} \) including the labeled and unlabeled samples are used for parameter learning.

Due to the subset of unlabeled data in the training database \( D_{Train} \), the Expectation-Maximization (EM-) algorithm \[77\] implemented in Netica is used to extract the parameters of the Bayesian network. The EM-algorithm is iterative and contains two steps \[172\]. During the first E-step, the expected values for all unlabeled samples \( P(u|y_1, ..., y_n, \theta^t) \) are calculated based on an initial set of parameters \( \bar{\theta}^t \) \[172\]. Considering these expected values as true, a new set of parameters \( \bar{\theta}^{t+1} \) is derived by maximum likelihood estimation in the M-step \[172\]. These two steps are iterated until a stopping criterion is completed.

### 4.2.6 Model Selection

A well-known scoring criterion for model selection amongst finite sets of models is the Bayesian Information Criterion (BIC) \[132, 77\], which scores the likelihood function and punishes the complexity of the model at the same time. Let \( D \) denote a database which contains \( n \) samples, \( \hat{\theta} \) denote the parameter estimator obtained by the EM-algorithm, and \( \text{Dim}[\hat{\theta}] \) denote the number of independent parameters \[172\]. The BIC score for a specific network structure \( G \) among the candidate models is defined as follows \[172\]:

\[
BIC(G : D) = \log P(D|G, \bar{\theta}) - \frac{\text{Dim}[\bar{\theta}]}{2} \log n, \tag{4.6}
\]

Let \( n \) contain \( n_{com} \) complete labeled samples \( (u^i, y^i), 1 \leq i \leq n_{com} \) and \( n_{inc} \) incomplete unlabeled samples \( (y^j) \) in \( D \), \( n = n_{com} + n_{inc} \) denote the sum of samples in \( D \). Given the current model, the log-likelihood \( \log P(D|G, \bar{\theta}) \) is given by \[172\]:

\[
\log P(D|G, \bar{\theta}) = \sum_{i=1}^{n_{com}} \log P(u^i, y^i|\bar{\theta}) + \sum_{j=1}^{n_{inc}} \log P(y^j|\bar{\theta}). \tag{4.7}
\]

For calculating the BIC score, the full training set \( D_{Train} \) including incomplete samples is used and the BIC scores for three candidate models are shown in Table 4.3. Compared to the naive Bayesian network and the fully connected Bayesian network, it can be seen that TAN classifier has the highest BIC score. In addition, it shows a reasonable trade-off between the required number of estimated independent parameters and log-likelihood. Therefore, the TAN classifier is selected among the three candidate models for the model of driver uncertainty.
4 Developing a Model-Based Lane Change Decision Aid System

Table 4.3: BIC scores for three candidate models based on 7000 training samples, first published in [172].

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-Likelihood</th>
<th>Independent Parameters</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive</td>
<td>-28258.50</td>
<td>73</td>
<td>-28398.85</td>
</tr>
<tr>
<td>TAN</td>
<td>-19368.59</td>
<td>559</td>
<td>-20443.29</td>
</tr>
<tr>
<td>Full</td>
<td>-18210.34</td>
<td>19999</td>
<td>-56659.39</td>
</tr>
</tbody>
</table>

4.2.7 Model Evaluation

With the selected structure of TAN classifier as well as the attributes, the model of driver uncertainty was implemented in the Netica Software. Figure 4.6 gives us an example of the interface of Netica environment with the model of driver uncertainty.

![Netica Interface](image)

Figure 4.6: The Screenshot of the model of driver uncertainty in Netica Software.

The remaining one third (40%) of the database \(D_{all}\) is used as a test database \(D_{Test}\) containing
4 Developing a Model-Based Lane Change Decision Aid System

4653 randomly selected samples. The test database $D_{Test}$ consists of 3054 labeled test data denoted as $D_{Test_l}$, that is used for evaluating the model, and 1599 unlabeled test data denoted as $D_{Test_u}$. In order to evaluate the model, the trained TAN classifier was tested to classify the remaining test samples $D_{Test}$. The performance of a binary classifier can be summarized in a 2x2 confusion matrix given a decision threshold $t_d$, which is shown in Figure 4.7 for the training data and test data at a decision threshold $t_d = 0.5$ [172]. Here the samples where the driver’s uncertainty state classified as “certain” are denoted as “positive samples”, and the samples where the driver’s uncertainty state classified as “uncertain” are denoted as “negative samples” [172].

![Figure 4.7: Confusion matrices for training data (left) and test data (right) of the TAN classifier (p/p’: positive samples; n/n’: negative samples), first published in [172].](image)

For evaluating binary classifiers, commonly used metrics based on the confusion matrix include accuracy, error rate, sensitivity, specificity etc. [79]. According to the concept of the model, the model of driver uncertainty should be able to recognize drivers’ uncertainty states, which means that the model should not only correctly recognize when drivers are uncertain, but also correctly classify when drivers are certain. Therefore, a metric which can correctly calculate the percentage of samples that are correctly classified is needed. The evaluation criterion of accuracy is chosen to evaluate the TAN classifier, as it can calculate the correctly classified samples, including the classification of the “uncertain” state for negative samples and the classification of the “certain” state for positive samples. Accuracy is defined as the proportion between correctly predicted positive or negative samples and the overall number of samples [172]. Let $N$ denote the total number of samples, $TP$ denote the number of correct predictions of “certain” states for positive samples, and $TN$ denote the number of correct predictions of “uncertain” states for negative samples, accuracy can be calculated as follows [172]:

$$\text{Accuracy} = \frac{TP + TN}{N} \quad (4.8)$$

The accuracy for all three models for the training data $D_{Train_l}$ (4632 labeled samples) and test data $D_{Test}$ (3054 labeled samples) at a decision threshold $\tau = 0.5$ is shown in Table 4.4. It can be seen that as the complexity of the candidate model increases, the accuracy of the training data increases, while the test data of TAN classifier has the highest accuracy of 0.78 [172]. Regarding

$^4$The decision threshold $\tau = 0.5$ is one of the used decision thresholds (see section 4.2.9) to classify the driver’s uncertainty state as either “certain” or “uncertain” from the outputs of the model.
Table 4.4: Accuracy of three candidate models for both training data and test data at a decision threshold $t_d = 0.5$, first published in [172].

<table>
<thead>
<tr>
<th></th>
<th>Naive</th>
<th>TAN</th>
<th>Full</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy for training data</td>
<td>0.76316</td>
<td>0.79037</td>
<td>0.80743</td>
</tr>
<tr>
<td>Accuracy for test data</td>
<td>0.76293</td>
<td>0.78028</td>
<td>0.78016</td>
</tr>
</tbody>
</table>

the trade-off between the accuracy and the number of independent parameters, TAN classifier has the best trade-off among the three candidate models [172].

Theoretically, the more parameters, the better you can model the training data, hence more parameters should lead to a higher accuracy [57]. However, this leads to overfitting, so that the model performs worse on the test data, as shown here in Table 4.4. Moreover, the accuracy of the training data among the models is rather similar. The fully connected BN only achieves an accuracy of 0.81 for the training data, it could be inferred that this is some sort of upper-limit of how well drivers’ uncertainty states can be discriminated.

### 4.2.8 Model Performance

The model of driver uncertainty can be utilized to the proposed MBLC Das that adapts its information behavior to driver uncertainty. As the proposed MBLC Das is supposed to support drivers with decision recommendations during lane changing, the model’s performance from the beginning of the lane change maneuver to the executed action in a time series is therefore essential. However, the model provides only the probability of driver uncertainty at the time of the reaction for each trial, it is difficult to have an overview of the model’s performance in a time series. With a frequency of 20 Hz, the actual TTC and distance gap between the subject vehicle and the approaching target vehicle as well as the lead vehicle at the first 5 seconds (100-time slots) are recalculated, based on the attributes in start conditions and reaction times. With 100 times inputs of attributes and 100 times of drivers' uncertainty scores after parameter learning in Netica, the performance of the model with the x-axis of time (s) and y-axis of the probability of the driver uncertainty can be generated and plotted. One example of model’s performance in the first 5 seconds is illustrated in Figure 4.8. In this example, the subject reacts very certain with a high score (5) and a short reaction time (0.8 s), which is in accordance with the high probability (0.9) of the driver’s uncertainty state classified as “certain” according to the model of driver uncertainty.
4.2.9 Classification of Drivers' Uncertainty States

Based on the obtained experimental data, a tree-augmented naive (TAN) Bayesian classifier is used as the model of driver uncertainty to recognize the probability of drivers' uncertainty states in a given lane change situation [77]. In order to integrate the model of driver uncertainty into the proposed MBLCDAS, a classification function is required to map the probability of driver uncertainty from the model at each time onto one of the drivers' uncertainty states ("certain" or "uncertain") in lane change maneuvers, to help trigger the HMI for the proposed MBLCDAS [171].

Let $X$ denote a set of discrete random variables which represents distance gap and TTC to the lead and the approaching vehicle [171]. For a given lane change situation which is encoded by $X = x$, the conditional probability can be inferred by the model of driver uncertainty: $P(U|X = x)$ [171]. Implemented in the driving simulator, the model is used in real time at a frequency of 60 Hz to estimate the conditional probability $P(U^t|X^t = x^t)$ with $t$ being the current point in time. Let $u^t_{pr} = P(U^t = 1|X^t = x^t)$ denote the probability where drivers are certain in their decision-making in lane change maneuvers [171]. Let $y^t$ denote the actual classification of driver uncertainty states as "certain"($y^t = 1$) or "uncertain"($y^t = 0$) [171]. Mapping $u^t_{pr}$ to $y^t$ can be described by a classification function $y^t = f_0(u^t_{pr})$ [171]. As a start, this classification function was tested based on a single threshold $t_d = 0.5$ and $I$ stands for the indicator function [171]:

$$f_0(u^t_{pr}) = I(u^t_{pr} > t_d) \quad (4.9)$$

However, the tests in the driving simulator show that the system performs often unstably with many
Developing a Model-Based Lane Change Decision Aid System

fluctuations [171]. Therefore, the additional classification function $y^t = f_1(u^t_{pr}, y^{t-1})$ needs to be added [171]. With reference to subjective uncertainty scores derived from the experiment, the areas where participants are relatively certain or uncertain are explored for additional decision thresholds in the plots of model's performance. It is found that the probability of driver uncertainty above $t_{dr} = 0.7$ where the rated subjective uncertainty score by participants is 5 and under $t_{df} = 0.3$ where the subjective uncertainty score is 1-3 are representative, which can then be used to classify the output of the model to “certain” and “uncertain” separately [171]. Depending on the prior classification $y^{t-1}$ at time $t - 1$ used for any given time $t > 0$, a rising threshold $t_{dr} = 0.7$ and a falling threshold $t_{df} = 0.3$ are chosen [171]. Hence, the classification function with the consideration of additional decision thresholds can be written as [171]:

$$f_1(u^t_{pr}, y^{t-1}) = y^{t-1} \cdot I(u^t_{pr} \geq t_{df}) + (1 - y^{t-1}) \cdot I(u^t_{pr} > t_{dr})$$ (4.10)

At time $t = 0$, the classification function $f_0(u^0_{pr})$ will be used [171]. If the probability of being certain $u^0_{pr}$ is above 0.5, the driver’s uncertainty state can be characterized as “certain” and as “uncertain” otherwise [171]. For the subsequent point in time $t > 0$, the final classification at time $t$ is then depending on the prior classification at time $t - 1$ and the classification function $f_1(u^t_{pr}, y^{t-1})$ will be used [171]. At the time of being classified as “uncertain”, $u^t_{pr}$ should increase above the threshold $t_{dr} = 0.7$, in order to be classified as “certain”; at the moment that the driver’s uncertainty state is classified as “certain”, $u^t_{pr}$ should decrease below the threshold $t_{df} = 0.3$ before it is classified as “uncertain” [171].

4.3 Decision Recommendation

In addition to the classification of drivers’ uncertainty states, the proposed MBLCDAS should also give helpful lane change suggestions via HMI regarding traffic safety: If it is safe to change the lane, the decision of overtaking will be suggested; if it is unsafe to change the lane, the decision of not changing the lane will be recommended. In the empirical experiment (section 3.5), participants’ subjective lane change decisions have been studied under three closing speeds (2.78 m/s, 4.17 m/s, 5.56 m/s) and nine TTCs (7.19 s, 8.63 s, 10.07 s, 11.51 s, 12.95 s, 14.39 s, 15.83 s, 17.27 s, and 18.71 s) with 29 participants, which is summarized in Figure 4.9 with the x-axis of distance gaps 5 for three closing speeds [171].

5The distance gap is selected as the x-axis of the plots for the action proportion of lane change decisions, because it is essential to help calculate the threshold for warnings given the closing speed. The calculated threshold can then be compared to the threshold for warnings in the ISO standard 17387.
According to the ISO 17387 [70] with regard to the performance requirements and the test of lane change decision aid systems, warnings for not changing the lane should be given when the TTC between the subject vehicle and the target approaching vehicle $\leq 7.5$ s. It is noticed that subjects still decide to brake in lane change situations where the TTC between the subject vehicle and the target vehicle $\geq 7.5$ s, although it is safe to change the lane according to the ISO standard 17387. In Figure 4.9, it implies that drivers’ subjective preferences are also important and need to be considered while providing suggestions for lane change decisions. Otherwise, mistrust can be induced if the system proposes to change the lanes in the given traffic situation whereas drivers already want to brake. Therefore, an action threshold $t_{sa}$ for each closing speed is needed to decide whether to suggest a
4. Developing a Model-Based Lane Change Decision Aid System

With reference to Figure 4.9, a minimal accepted distance gap is looked for each closing speed, below which participants prefer to brake. The distance gaps of 36 m, 42 m, and 48 m for the corresponding closing speeds of 2.78 m/s, 4.17 m/s and 5.56 m/s are chosen and used as a basis for deriving the function of decision recommendations, in which over 90% of participants have decided not to change the lane with the braking action [171]. With these three minimal distance gaps and the corresponding closing speeds, the relationship between distance gap \(d_{gap}\) and closing speed \(v_{close}\) can be generalized as a linear function [171]:

\[
v_{close} = -5.56 + 0.232 \times d_{gap}
\]  

(4.11)

The closing speed at time \(t\) is denoted by \(v_{close}^t\) and the decision recommendation is denoted by \(z^t\), which is either characterized as the recommendation for changing the lane \((z^t = 0)\) or the recommendation for a no lane change decision \((z^t = 1)\), a classification rule is used \(z^t = g(v_{close}^t, d_{gap}^t)\), where [171]:

\[
g(v_{close}^t, d_{gap}^t) = \begin{cases} 
1 & \text{if } v_{close}^t < -5.56 + 0.232 \times d_{gap}^t, \text{ and } d_{gap}^t > 24 \\
0 & \text{else}
\end{cases}
\]

(4.12)

Compared to the warning criteria from ISO 17387, the selected action thresholds recalculated in TTC for the corresponding closing speeds are much longer and therefore can provide sufficient traffic safety. With this classification function, the proposed MBLCDAS can recommend not to change a lane if the distance gap is too small for the current closing speed or to provide a suggestion of changing the lane otherwise. In addition, with the consideration of drivers’ preference for providing lane change decisions, the classification function for the proposed MBLCDAS is user-centric and is expected to help in building driver trust in the proposed MBLCDAS.

4.4 Human Machine Interface

In order to convey the information of the drivers’ uncertainty states provided by the model and the recommendation for lane change decision provided by the classification function to drivers, a Human Machine Interface (HMI) is needed for the proposed MBLCDAS.

Regarding the interface design of the lane change decision aid systems with Blind Spot Warning function in the market, a flashing light in vehicle is usually used as an indicator to warn drivers of the presence of the other vehicle in the blind spot. The light is placed either on the (in/out) side view mirror such as the Blind Spot System offered by Ford, Audi etc. or the A-pillar that separates the door window and the windscreen, e.g., Volvo’s Blind Spot Information System [1]. In addition to the flying light, some car manufacturers also provide an acoustic signal to warn drivers of the potential danger during changing the lane, e.g., Nissan’s Blind Spot Warning system [2]. As supplements to the flashing light used in the existing lane change decision aid systems, recently different concepts...
of interface design for lane change assistance systems have been developed. Habenicht has developed a maneuver-based lane change assistance system and visualized the advice on a display with visual elements such as arrows [53]. Besides, a Cooperative Lane Change Assistant has been developed using the head-up display to assist drivers to find the appropriate gaps and cooperate with other drivers in lane change maneuvers [75]. Ambient light displays are also introduced to support driver’s lane change decisions [91]. For the modality of the proposed MBLCDAS, only the visual element is taken into account, as the acoustic element may be annoying [53]. Ambient light is also not considered, as it is unclear whether the ambient light is perceived in the periphery only, which makes it difficult to study the actual effect of ambient light displays on driver behavior.

As the lane change maneuver is a time-demanding driving task, it is important that the visual elements in the interface can be rapidly perceived by drivers. To ensure this fast visualization, two different aspects have been considered:

- The first aspect is symbol. Especially, the symbol of the emotional face strongly used in information visualization has been paid attention to, as it can be interpreted intuitively and rapidly [155]. Frischen et al. also show that humans can process emotional faces rapidly and almost with no effort [49].
- The second aspect is color, which is additionally used as it can be perceived preattentively (in millisecond range) by humans [147]. Furthermore, it is stated that the color is often the most efficient attribute for visualizing information that needs to be quickly perceived [29].

Therefore, the symbols, which have abstract faces with different colors and emotional expressions designed by the project partner DLR, are adopted in HMI design and used to convey the corresponding information to drivers [171]. Regarding the proposed MBLCDAS that considers driver uncertainty as well as traffic safety and the described two aspects for fast visualization, symbols are encoded by emotional expressions and colors [171].

### 4.4.1 Emotional Expression

For emotional expressions, two emotional faces are considered: a “happy” face with a smile and the thumb up representing a recommendation to change the lane and an “unhappy” face with closed eyes and two hands in front representing a recommendation of not changing the lane (see Figure 4.10) [171].

### 4.4.2 Color

The existing lane change assistance systems using traffic light colors (amber, green and red) to describe only the criticality of the traffic situation, such as the Lane Change Decision Aid Systems with the Blind Spot Warning function use amber (e.g., Buick’s indicator for Blind Spot Warning) or red color (e.g., Mercedes’s Blind Spot Assist) to warn the driver of the potential danger in the blind spot [47]. Different from the existing LCDASs, the proposed MBLCDAS uses red, green, and transparent

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6http://www.dlr.de/dlr/de/desktopdefault.aspx/tabid-10002/
colors to represent both criticality and driver uncertainty. The transparent color is used to show the system’s conservatism when drivers are certain during decision-making in lane change maneuvers [171]. The green color is meant to show the system’s activism to help drivers when drivers are uncertain [171]. The red symbol describes the criticality of the traffic situation, regardless of whether the driver is certain or uncertain due to the priority of the criticality [171]. The three used symbols are shown in Figure 4.10.

Figure 4.10: The transparent symbol is shown when changing the lane is safe and drivers are certain; the green symbol is shown when changing the lane is safe and drivers are uncertain; the red symbol is shown when changing the lane is unsafe regardless of drivers’ uncertainty states (This graphic is first published in [171]).

4.4.3 Position and Size

Oriented by the existing lane change decision aid systems that place the flashing light on the (in-/out) side view mirror [1], the symbols designed for the proposed MBLCDAS are placed at the right corner in the left side mirror in the early design phase. But this fixed position forces drivers to switch their gazes between the displayed symbol and the approaching vehicle in the left side mirror, which means that drivers need extra visual effort and takes a long time to perceive the symbol. To solve this problem, the symbols are designed to be placed directly next to the rear approaching vehicle in
the left side mirror, which moves together with the rear approaching vehicle and is expected to mini-
mize the drivers’ visual effort to perceive symbols displayed in the left side mirror (see Figure 4.11) [171]. Based on the classification of drivers’ uncertainty states and the classification of lane change decisions, four possible configurations of the symbols representing criticality and driver certainty are displayed in the left side mirror (see Figure 4.11) [171]:

- When drivers are classified as certain during decision-making and changing the lane is clas-
sified as safe, the transparent symbol is shown in the left side mirror (see Figure 4.11, above left).
- When drivers are classified as uncertain during decision-making and the lane change is clas-
sified as safe, the green symbol is shown in the left side mirror (see Figure 4.11, above right).
- When drivers are classified as uncertain during decision-making and the lane change is clas-
sified as unsafe, the red symbol is displayed in the left side mirror (see Figure 4.11, below right).
- When drivers are classified as certain during decision-making and the lane change is clas-
sified as unsafe, the red symbol is displayed in the left side mirror (see Figure 4.11, below left).

Figure 4.11: Four configurations of the symbols representing criticality and driver certainty for the proposed MBLCDAS in the left side mirror in the driving simulator: the approaching vehicle in the left lane with the moving symbol next to it, first published in [171].
The symbol displayed in the left side mirror has a width of 96 pixels and height of 96 pixels. With a three-dimensional model, it can be embedded in the driving simulator environment. The symbol is placed next to the approaching rear vehicle. On real motorways, if the approaching rear vehicle approaches, its visual size will be smaller when it is far away. In line with this, the size of the symbol is also dependent on the distance gap $d_{\text{gap}}$ between the subject vehicle and the approaching rear vehicle. After testing in the driving simulator, the actual size of the symbol with the X and Y coordinate denoted as $s_{x,y}$ can be scaled with the following formula: 

$$s_{x,y} = s_{o x,y} \times \left( \frac{d_{\text{gap}}}{104} \times 0.6 + 0.65 \right).$$

In the formula, $s_{o x,y}$ is the original size of the symbol without any scaling (96*96 pixels). $d_{\text{gap}}/104$ represents the normalized distance gap. 0.6 is a coefficient for the relative change of the symbol’s size, while 0.65 is the constant that decides the minimum size of the symbol.

### 4.5 Implementation

To implement the prototype of the proposed MBLCDAS in the driving simulator, Data Processing Units (DPU) in SILAB software are used. In a DPU, Dynamic Link Library (DLL) files are packed in program units. The port of the DPU including inputs and outputs can be freely defined and connected in the addressed configuration file. Based on this, the model of driver uncertainty in Netica can be connected to the DPU in SILAB, where the selected four attributes of the model are connected to the corresponding ports of DPU. Similarly, the symbols of the HMI can be displayed in the left side mirror using the DLL files in SILAB.

### 4.6 Summary

With the aim of developing a lane change assistance system that adapts to both criticality and driver uncertainty during decision-making in lane change scenarios on simulated two-lane highways, a probabilistic model of driver uncertainty to classify whether a driver is certain or not in the given traffic situation has been developed. According to the criterion of BIC and accuracy, the TAN classifier has been selected among three candidate Bayesian networks to infer drivers uncertainty states during decision-making in lane change maneuvers, as it maximizes the BIC score and has the highest accuracy on the test data (accuracy = 0.78). The accuracy of 0.78 means that the chosen TAN classifier can correctly recognize drivers’ uncertainty states (“certain” or “uncertain”) in a majority, which indicates a promising result [172]. However, the limitation of the model of driver uncertainty is that it is a static BN representing the static relationship between each “snapshot” of the traffic situation made at the time of participants’ decisions and their subjective uncertainty scores [172]. It cannot recognize drivers’ uncertainty states dynamically due to the difficulty in dynamically measuring driver uncertainty in experiments [172]. In future work, more complex models such as Dynamic Bayesian Networks can be considered [77].

The drivers’ uncertainty states can be classified by the probabilistic model, whereas the recommendation for lane change decisions can be classified by the safety analysis based on drivers’ preferences. They together trigger the corresponding information displayed on the HMI. Compared to existing lane change assistance systems which use traffic light colors to encode criticality and...
provide mainly warning functions, the proposed MBLCDAS uses colored abstract faces with emotional expressions encoding both criticality and driver uncertainty to provide suggestions for lane change decisions. The model of driver uncertainty is intended to be used to develop the proposed MBLCDAS that can recognize drivers’ uncertainty states during decision-making in lane change situations. After developing the model of driver uncertainty, classifying driver uncertainty states and lane change decisions, and the corresponding HMI design, a lane change assistance system that adapts to driver uncertainty states (MBLCDAS) during decision-making in lane change maneuvers has been developed.

To evaluate the developed MBLCDAS, an evaluation study, which aims to compare the reduction of reaction times and also the building of trust between the developed MBLCDAS and reference systems without considering driver uncertainty, will be introduced in chapter 5.
5 Evaluating the Model-Based Lane Change Decision Aid System

With the developed MBLCDAS, the research hypotheses ($H_2$, $H_3$, $H_4$) regarding the reduction of driver uncertainty and the building of trust in chapter 2 can be examined. In this chapter, an evaluation study comparing the developed MBLCDAS and other reference systems that do not consider driver uncertainty is introduced, with regard to the reduction of reaction times and the building of trust. This chapter starts from related work on the building trust in automation (section 5.1). In section 5.2, the hypothesis and research questions for this study are introduced, followed by the methods of the evaluation study (section 5.3). In sections 5.4 and 5.5, results of the evaluation study and a summary of this chapter are given.

5.1 Related Work

Reviewing literatures on how trust is built in the context of human machine interaction, one classical human factors approach is the warning approach that gives warnings when specific parameters are violated [19]. However, it works well only in clear situations where the sensor data are reliable. For unclear situations where automation is imperfect, presenting automation information or uncertainty is proposed. In line with this and regarding the impact of presenting automation ability on trust, there are two studies conducted with an ACC (Adaptive Cruise Control). Seppelt and Lee [133] studied the effect of visualization of the adaptive cruise control (ACC) behavior on reliance and transitions between manual and ACC control with 24 participants in a driving simulator. The results showed that participants had more reliance on ACC with the presented information about ACC than the control group without displaying the information of ACC. In addition, Verberne et al. studied the impact of sharing driving goals and giving information on trustworthiness and acceptability of ACC in a driving simulator with 57 participants [151]. The results showed that ACCs were rated more trustworthy and acceptable when they shared the driving goals of the user and provided information of the ACC.

Regarding presenting automation uncertainty, Beller et al. [19] conducted a driving simulator study with 28 participants with varied presentations of uncertainty information and automation reliability. The results showed that the presentation of uncertainty information increased the time to collision when automation failed and led to higher trust ratings and increased acceptance. Similar results were also found by Helldin et al. [59], who investigated the effect of presenting car uncertainty on driver trust in an automated driving scenario with 59 participants. The results indicated that drivers who were informed of the uncertainty information had more driving safety and calibrated a more proper trust than the control group without receiving any information.
In addition to the presentation of automation uncertainty, perceived anthropomorphism has also been shown to increase the building of trust. In Waytz et al.'s experiment [157], one hundred participants took part in the driving simulator study, where they drove either a normal car, an autonomous car which can control steering and speed or an autonomous vehicle integrated with anthropomorphic features: name, gender, and voice. Compared to conditions without a humanlike mind, participants in the anthropomorphic condition trusted their vehicle more, were more relaxed in accidents and blamed other drivers less for accidents.

To the author's knowledge, there is no work that builds driver trust by adapting to drivers’ uncertainty states during decision-making in lane change maneuvers.

5.2 Hypothesis and Research Questions

A general approach to the building of human trust in automation is to transfer trust theories between humans to trust in automation [85]. As introduced in the theoretical background, this work is inspired by the “emancipation” theory of trust in social psychology, which implies that when humans are uncertain in a social situation, they tend to trust partners to set him/her free from this uncertainty [170]. With the consideration of the partners’ uncertainty state and transferring this trust theory into the automotive domain, it is assumed that if drivers are uncertain during decision-making process and assistance systems can help reduce their uncertainty with useful advice timely, drivers will tend to build trust in assistance systems.

With the goal of evaluating the developed MBLCDAS that adapts to drivers’ uncertainty states [171] regarding the reduction of reaction times and the building of trust, this study aims to investigate the following research questions, which are also the addressed research questions (RQ 2, RQ 3, RQ 4) at the end of chapter 2 [173]:

- RQ 1: Compared to the driving without any assistance, can the developed MBLCDAS reduce reaction times during decision-making in lane change maneuvers?
- RQ 2: Can trust be built between driver and the developed MBLCDAS that adapts to driver uncertainty?
- RQ 3: Is the developed MBLCDAS that adapts to drivers’ uncertainty states more trusted and accepted than other reference systems that do not consider driver uncertainty?

5.3 Method

In order to answer the research questions above, a driving simulator study focusing on a specific lane change scenario on two-lane motorways was conducted [173], which is depicted in Figure 5.1. The subject vehicle (A) driving with a constant speed of 130 km/h approaches a lead vehicle (B) traveling with a constant speed of 100 km/h both in the right lane, while a third rear target vehicle (C) in the left lane is closing the gap with the subject vehicle with a constant speed of 140 km/h in varied distances [173].
5 Evaluating the Model-Based Lane Change Decision Aid System

![Simulated Lane Change Scenario](image)

Figure 5.1: The simulated lane change scenario for the evaluation study: The subject vehicle (A) driving at 130 km/h approaches a slower lead vehicle (B) driving at 100 km/h, while a faster rear target vehicle (C) driving at 140 km/h approaches the subject vehicle (A).

5.3.1 Participants

20 recruited volunteers (5 males, 15 females) from the C.v.O University of Oldenburg with an average age of 24.3 years (SD = 6.5 years) took part in this experiment [173]. They owned a valid German driver license and had an average driving experience of 6.7 years (SD = 6.3 years) [173]. Totally 15 euros were given to participants for their 90-minute participation [173].

5.3.2 Apparatus

The experiment was done in a fixed based driving simulator at the OFFIS Institute for Information Technology. Three projection surfaces provided a field of view of approximate 150 degrees for a simulated 3D-environment [173]. Exterior mirrors and the instruments were simulated on tablets embedded in the mockup [173]. The driving simulation software SILAB was used to generate the simulation environment [173]. In addition, a game controller was used to collect response actions of the participants indicating participants' lane change decisions (Figure 5.2) [173]. It is noticed that all vehicles including the subject vehicle drive autonomously and participants only need to make lane change decisions by pressing buttons (see the top side of the game controller in Figure 5.2) in the game controllers without actually accelerating or braking.
5 Evaluating the Model-Based Lane Change Decision Aid System

Figure 5.2: Participants’ perspective in the driving simulator (left). Front side (right above) and top side (right below) of the game controller. On the top side of the game controller: Buttons on the left indicate steering actions representing the decision of changing the lane and buttons on the right indicate braking actions for no change decisions. This graphic is first published in [173].

5.3.3 Experimental Design

There are five experimental conditions: baseline condition, proposed system C that refers to the developed MBLCDAS, and three reference systems (A, B, D). For the experiment design, a 5*5 Latin square design (see Table 5.1) with repeated measures was considered to counterbalance the potential ordering effect between the experimental conditions (baseline, system A, system B, system C and system D) [173]. Each row can be treated as one order of the experimental conditions. Every four subjects were assigned to the same order of experimental conditions and each subject tested all experimental conditions [173]. The experiment took about 90 minutes.

In total, 8 lane change situations differing in the distance gap (30 m to 78 m with 6 m interval except 66 m) between the approaching vehicle and the subject vehicle at the closing speed of 4.17 m/s were tested and each of them was repeated ten times for each experimental condition within each subject. In situations at the distance gap of 66 m, the blinks between transparent symbol and the green symbol were too frequent when the approaching vehicle closed the gap, which may lead to confusion of participants’ understanding of the function of the proposed system C. Therefore, the distance gap of 66 m was excluded from the evaluation study.
Table 5.1: A 5*5 Latin square design with the assignments of experimental conditions (“A”, “B”, “C”, “D” stand for the system A, system B, system C, and system D; “E” stands for the baseline).

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>E</td>
<td></td>
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<tr>
<td>B</td>
<td>C</td>
<td>D</td>
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<td>A</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>D</td>
<td>E</td>
<td>A</td>
<td>B</td>
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<tr>
<td>D</td>
<td>E</td>
<td>A</td>
<td>B</td>
<td>C</td>
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<tr>
<td>E</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td></td>
</tr>
</tbody>
</table>

To answer RQ 1 regarding the reduction of reaction times and RQ 2 regarding the building of trust, an unassisted baseline condition is needed to be compared with the proposed system C [173]. Considering RQ 3, a set of reference lane change assistance systems that do not consider driver uncertainty is required to be compared to the proposed system C [173]. Three reference systems (system A, system B, system D) are considered. The reference systems A and B only consider criticality and are designed with reference to the existing lane change assistance system focusing on the warning functions [173]. Compared to reference systems A and B using only two symbols, the proposed system C uses three symbols. It means that if there is an effect between system C and reference systems (A or B), it will be difficult to decide whether the effect comes from the integration of the model of driver uncertainty or the use of an additional symbol [173]. For this reason, a third reference system D utilizing a same set of symbols as the proposed system C is taken into account [173]. The detailed descriptions of system C, system A and system B, and system D will be given in the following paragraphs.

In chapter 4, the proposed lane change assistance system C (MBLCDAS) using three symbols (Figure 5.3) has been introduced, which can describe criticality and driver uncertainty based on the model of driver uncertainty:

- If a lane change is safe and drivers are certain during decision-making, the system will display a transparent symbol to suggest changing the lane in a conservative way [171].
- If a lane change is safe and drivers are uncertain during decision-making, the system will display a green symbol to suggest changing the lane in an active way [171].
- When lane change is unsafe, the system will display the red symbol to give suggestions of not changing the lane in an active way [171].
System A and system B both have two symbols, including the same red symbol and another different symbol. The red symbol is used to give suggestions for not changing the lane when the lane change is unsafe (see Figure 5.4)[173]. For suggesting to change the lane when changing the lane is safe, system A uses a transparent symbol with less salient character to show its defensive character, while system B uses a more silent green symbol to show its offensive character [173].

Contrary to the proposed system C presenting symbols that depend on drivers’ uncertainty states (“certain” with the transparent symbol or “uncertain” with the green symbol) based on the model of driver uncertainty, the reference system D does not use the model of driver uncertainty [173]. Instead, it uses a fixed time delay of 1.2 seconds between the presentation of the transparent symbol and the green symbol [173]. The time delay of 1.2 seconds was chosen as the average time to perceive the first transparent symbol presented in the left side mirror, which was calculated based on estimated perception times in [112] and then tested with three automotive experts in the driving simulator. For the system D, the transparent symbol will always be shown at the beginning of each trial when the lane change is safe [173]. If the lane change is still safe after 1.2 seconds, the transparent symbol will change to the green symbol. If the lane change is unsafe after 1.2 seconds, the red symbol with the suggestion of no lane changes will be presented [173].

It is noted that although these four systems are different in providing recommendations for lane change decisions presented by different symbols, the same action thresholds are used to decide whether the given traffic situation is safe or unsafe to perform a lane change [173], which indicates that the red symbol is used in the same way for all four systems.
5.3.4 Procedure

After signing an informed consent and writing down the information about age, gender, driving experience, and driving miles in the demographic questionnaire, participants were asked to read a handout with safety instructions and the experimental procedure [173]. They were instructed that the task was to decide for a lane change in different situations and they would drive either without any assistance or with assistance systems. Participants were told that four lane change assistance systems (A, B, C, and D) were designed to help their decision-making in lane change maneuvers and they could decide themselves, whether they would follow the system’s advice [173]. Subjects were automatically assigned to one order of all conditions in sequence based on the assignment of Latin square design in Table 5.1 [173]. A handout (see Appendices) with the explanation of the symbols concerning the action suggestions presented on the HMI was provided before driving in the experimental condition containing an assistance system [173]. Especially, as there was no explicit description of driver uncertainty on system C, participants were not aware that the system C was the system that considered driver uncertainty [173]. After reading through the handout about the systems, participants were given time to familiarize with the driving simulator and the game controller. A training session of 10 trials with the first experimental condition followed [173]. Participants were instructed that they did not have to actually drive, but show their lane change decisions through pressing buttons in the game controllers.

At the beginning, participants in the subject vehicle (A) were instructed to follow the lead vehicle (B) and look at it while driving [173]. After 4.5 seconds, an acoustic signal was provided and at the same time, the approaching vehicle (C) in the left lane appeared in the left side mirror [173]. After the acoustic signal, participants were asked to look at the left side mirror to estimate the possibility of doing a lane change [173]. If they found it was possible to change the lane in front of the approaching vehicle, they had to press the left button on the top side of the game controller (Figure 5.2) to indicate their decisions for changing the lane; otherwise, if participants thought that it was not possible to overtake in front of the approaching vehicle (C), they had to press the right button to indicate the decision for no lane changes [173]. To make sure that the measurement of the reaction time was precise [173], the press of buttons in the game controller was chosen in the driving simulator, instead of truly changing the lane with the steering wheel or accelerating with the braking pedal.

After pressing one of the buttons on the top side of the game controller, both the lead vehicle (B) in the right lane and the approaching vehicle (C) in the left lane disappeared and the next trial began [173]. Participants were not forced to decide as quickly as possible, i.e. no additional time pressure was imposed [173]. They should behave as usual as possible on motorways [173]. After finishing an experimental condition with a system, participants had to fill out a questionnaire with 11 questions [173], which were adapted from the Jian et al.’s trust questionnaire [71]. As all systems use the same action threshold for determining the criticality and make no errors of giving suggestions of either changing the lane or not, it is assumed that the differences between systems collected from questionnaires may be difficult to be found [173]. To be able to compare the four systems regarding the helpfulness, trust, and acceptance, a structured interview was conducted at the end of the experiment with three questions [173, p. 532]:

- “In comparison to driving without systems, are the four assistance systems helpful in the lane change decisions?”
5 Evaluating the Model-Based Lane Change Decision Aid System

- “In which system do you build most trust?”
- “Which system is most accepted?”

It was noticed that participants were also asked to give corresponding reasons for the last two questions [173].

5.3.5 Data Collection

To answer the research questions, measurements of reaction time and the building of trust were considered. The reaction time was measured from the acoustic signal which triggered the start of a trial until participants pressed one of the buttons on the game controller [173]. Different from reaction times, trust usually cannot be measured directly and objectively, instead, questionnaires or interviews (e.g., Jian et al.'s trust questionnaire [71]) were used to measure trust qualitatively. In the experiment, besides the qualitative measurement of trust, two surrogate measurements denoted as the 1) follow rate or rate of agreement (RoA) and the 2) follow time (FT) were proposed as quantitative measures of trust [173]. These two measurements of trust separately represented how often participants followed systems’ suggestions and how fast they followed the advice. For each assistance system, RoA is defined as the ratio between the number of trials in which participants choose the same maneuver as suggested by the assistance system (Number of Agreements: NoA) and the number of all trials (N), RoA = NoA / N [173]. In contrast to reaction times which were calculated from all actions regardless of whether participants actually follow systems’ suggestions, FT was calculated only from the subset of trials, in which participants followed the systems’ suggestions.

According to the research hypothesis, it is assumed that if participants have built trust in assistance systems, they will tend to agree with the systems’ suggestions and then follow them [173]. The more trust that participants have built with systems, the more often and quicker they follow the advice [173]. As it is difficult to distinguish whether participants actually agreed with and followed the systems’ suggestions from whether suggestions were simply conformed to participants’ decisions but had no influence on them, a “hypothetical” RoA and FT are proposed and calculated using the trials from the baseline condition [173]. The trials of the baseline condition were used to calculate the “hypothetical” RoA and FT for the baseline condition, which can be compared with the actual RoAs and FTs of the four assistance systems [173]. To calculate the “hypothetical” RoA and FT, action thresholds for decision recommendation (see section 4.3) were used to decide which lane change decisions should be suggested [173]. Regarding examining the actual influence of action suggestions on driver’s current lane change decisions, a distinct difference between the actual RoAs and FTs derived from the assisted conditions and the hypothetical RoA and FT derived from baseline condition was expected.

5.4 Results

The data collected from the driving simulator was used to calculate reaction times, FT, and the NoA required for calculating the RoA [173]. The data were analyzed in R (https://www.r-project.org/).
Table 5.2 shows a summary of Mean Reaction Time (MRT), RoA and FT for five experimental conditions.

Table 5.2: Summary of results (MRT: Mean Reaction Time; RoA: Rate of Agreement; FT: Follow Time; *: hypothetical), first published in [173].

<table>
<thead>
<tr>
<th>Measure</th>
<th>System A</th>
<th>System B</th>
<th>System C</th>
<th>System D</th>
<th>Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRT (s)</td>
<td>1.99</td>
<td>2.00</td>
<td>1.97</td>
<td>1.83</td>
<td>2.07</td>
</tr>
<tr>
<td>RoA (%)</td>
<td>85.4</td>
<td>84.4</td>
<td>87.6</td>
<td>87.3</td>
<td>81.6*</td>
</tr>
<tr>
<td>FT (s)</td>
<td>1.98</td>
<td>1.98</td>
<td>1.94</td>
<td>1.80</td>
<td>2.02*</td>
</tr>
</tbody>
</table>

5.4.1 Mean Reaction Time

In comparison to the baseline condition, all four assistance systems can reduce reaction times [173]. In Table 5.2, it can be seen that reference system D results in the best average reduction of 0.24 s while the proposed system C has the second best average reduction of 0.1 s [173]. As the effects of the rows and columns are also treated as factors for Latin square design with repeated measures, a three-way ANOVA was conducted to test the effect of experimental conditions, columns and rows of the Latin square design on the reaction times [173]. The result of the analysis shows that there is a significant effect of the experimental condition ($F(4, 72) = 3.90, p = .006$) on reaction times [173]. No significant effects have been found from the columns and rows of the Latin square design on reaction times, which indicates the absence of learning effect and the effect of individual differences in groups [173].

A post-hoc pairwise t-test with Bonferroni adjustment of p-values was conducted to find out which conditions have the actual significant difference of the reaction time [173]. The result of the post-hoc test shows that there are significant differences between the baseline and other four conditions ($p < 0.05$), as well as between system D and other four conditions ($p < 0.01$) [173].

5.4.2 Rate of Agreement and Follow Time

Regarding RoA, it is noticed that compared to the baseline condition, all systems are able to increase the RoA and the proposed system C has the highest RoA of 87.6%, which increases the hypothetical RoA by 6% [173]. Because the RoA is a summary of NoA and cannot be directly used for testing the significance of experimental conditions [173]. The NoAs are used for conducting a Friedman test to compare the differences of the RoA of different systems [173]. The result of the Friedman test shows that there is a significant difference among the distribution of the five experimental conditions ($\chi^2(4) = 49.893, p < .01$)[173]. A post-hoc Wilcoxon test with Bonferroni correction shows that there are significant differences between system C and B ($p < 0.01$) as well as between the baseline condition and systems A, C and D ($p < 0.01$) [173].
Regarding the follow time, a three-way ANOVA with repeated measures was used to test the effect of experimental conditions on FT [173]. The result indicates a significant effect of the experimental condition on the FT ($F(4, 72) = 3.29, p = .02$) [173]. A post-hoc pairwise t-test with Bonferroni adjustment of p-values shows that there is a significant difference in FT between system D and all other four conditions ($p < .05$), but no significant difference with system C [173].

### 5.4.3 Questionnaire and Interviews

After driving with an assistance system, participants were asked to complete a questionnaire with 11 questions which were adjusted from Jian et al.’s trust questionnaire [71]. They needed to rate the system with respect to the system’s reliability, safety, sympathy, efficiency, the subjects’ expectancy, acceptance, and trust with scores from 1 (no agreement) to 7 (full agreement) [173]. A summary of the mean values of all 11 questions, with the keyword representing each question and the highest score in bold, is shown in Table 5.3.

Table 5.3: Summary of the trust questionnaires with mean values of 11 questions for each system (A, B, C, D: system A, B, C, D) and for all systems (T: Total), first published in [173].

<table>
<thead>
<tr>
<th>Focus of questions</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>Understandability</td>
<td>6.2</td>
<td>6.0</td>
<td>5.8</td>
<td>5.4</td>
<td>5.8</td>
</tr>
<tr>
<td>Confidence</td>
<td>5.2</td>
<td>5.1</td>
<td>5.3</td>
<td>5.0</td>
<td>5.1</td>
</tr>
<tr>
<td>Reliability</td>
<td>5.3</td>
<td>5.5</td>
<td>5.3</td>
<td>4.8</td>
<td>5.2</td>
</tr>
<tr>
<td>Traffic safety</td>
<td>4.9</td>
<td>5.3</td>
<td>5.0</td>
<td>5.1</td>
<td>5.1</td>
</tr>
<tr>
<td>Efficiency</td>
<td>4.5</td>
<td>5.0</td>
<td>4.7</td>
<td>4.5</td>
<td>4.6</td>
</tr>
<tr>
<td>Sympathy</td>
<td>4.8</td>
<td>4.6</td>
<td>4.5</td>
<td>4.4</td>
<td>4.4</td>
</tr>
<tr>
<td>Support on time</td>
<td>4.8</td>
<td>5.0</td>
<td>4.7</td>
<td>4.9</td>
<td>4.8</td>
</tr>
<tr>
<td>Expectancy</td>
<td>4.9</td>
<td>5.0</td>
<td>4.8</td>
<td>4.8</td>
<td>4.9</td>
</tr>
<tr>
<td>Acceptance</td>
<td>4.8</td>
<td>5.1</td>
<td>4.9</td>
<td>4.7</td>
<td>4.9</td>
</tr>
<tr>
<td>Follow the system</td>
<td>3.1</td>
<td>3.4</td>
<td>3.6</td>
<td>3.0</td>
<td>3.3</td>
</tr>
<tr>
<td>Trust</td>
<td>4.5</td>
<td>4.7</td>
<td>4.9</td>
<td>4.6</td>
<td>4.7</td>
</tr>
</tbody>
</table>

Concerning the questions about reliability, traffic safety, efficiency, etc., it is noticed that the reference system B is more preferred than other systems [173]. But regarding the questions related to the willingness to follow the system’s advice and the building of trust, it is found that the proposed system C is more preferred than other systems [173]. Besides, it is rated by participants that they are most confident in system C, implying that they tend to trust system C more than other systems [173]. But it can be seen that the difference between all systems is relatively small. A one-way
5 Evaluating the Model-Based Lane Change Decision Aid System

ANOVA was done to compare the scores among the four systems and no significant results among four assistance systems were found [173]. Additionally, a structured interview was performed after filling out all questionnaires, to let each participant choose a single preferred system regarding the helpfulness, trust, and acceptance [173]. Compared to the baseline condition without any assistance, all systems are found to be helpful. Regarding the building of trust and acceptance, system C is chosen by 55% of participants as the favorite system with more acceptance and trust than other three reference systems (A: 20%, B: 20%, D: 5%) [173].

5.5 Summary

Giving a summary of the results, it can be concluded that the proposed system C that adapts to driver uncertainty can both reduce reaction times and build driver trust in the system [173]. The proposed concept of building trust in automation by adapting its information behavior to driver uncertainty, which is inspired by the emancipation theory of trust, is demonstrated [173].

Concerning the RQ 1 of reducing reaction times, it is shown that the proposed system C can reduce long reaction times by an average of 0.1 s in comparison to the baseline condition without any assistance [173]. Concerning the RQ 2 of trust building, the proposed system C can increase the Rate of Agreement by 6 % in comparison to the hypothetical RoA treated as the baseline with respect to the agreement of the system's suggestion [173]. With the assumption that the RoA is a potential indicator for the building of trust and also according to the participants' qualitative feedback from interviews, it can be concluded that trust has been built in the proposed system C [173].

In addition to the research questions, it is also interesting to compare the proposed system C containing three symbols with the reference system A and B consisting of two symbols. In general, three symbols are more preferred by participants than two symbols. Especially, drivers with less driving experience (< 1 year) report that three symbols are very helpful in supporting their decision-making [173]. Besides, it is noticed that regarding RoA, the proposed system C is significantly different from the reference system B, but it has no significant difference with reference system A. It implies that the preference of proposed system C over a silent system consisting of two symbols and indicates that the unobtrusive system is more preferred than the obtrusive system (perceived as annoying), which are consistent with the statements listed by participants in interviews [173].

Apart from this, it is also important to compare system C and system D that both contain three symbols. Concerning the quantitative results, the performance of system C and system D on reaction times, RoA and FT have no large differences. However, regarding the qualitative feedback from the interviews, system C is more accepted and trusted than system D. Based on participants’ feedback in interviews, there can be two possible reasons. First, due to the description of the handout for system D stating that both the transparent symbol and the green symbol stand for “Overtaking is safe, please turn left”, participants are to some extent confused about the function of system D and then have an initial bad impression on system D [173]. On the other hand, the transition from the transparent symbol to the green and red symbol of system D is reported by some participants as
too fast, which can also potentially influence their impressions on system D [173]. Although system D has the shortest reaction time, it is the least accepted and trusted among four systems, which implies that the reaction time alone cannot reflect the acceptance or trust in the system [173]. The shortest reaction time with system D may simply come from the fixed time delay effect, which imposes participants to react to symbols unconsciously [173]. The small difference between system C and system D may be caused by the limitation of the model of driver uncertainty, and a better model taking all relevant parameters into account may induce a significant difference between them [173].

In comparison to the field studies, the current conducted simulator study is limited, as the perception of traffic information in the driving simulator is different from real roads, which can lead to different driver behaviors [173]. Besides, the use of the fixed setting with the game controller is reported as unnatural by some participants in the evaluation study [173]. As they show their lane change decisions only by pressing buttons on the game controller in the experiment, instead of actually using the steering wheel or brake pedal [173].

As a supplement to the qualitative measurement of trust by questionnaires and interviews, the rate of agreement reflecting the agreement and follow time are proposed as surrogate measures of trust. It is difficult to make sure that the agreements with the systems’ suggestions lay on the built trust in systems or just the fit of suggestions to the current situation [173]. To solve this problem, a hypothetical RoA derived from the baseline condition is introduced to compare with RoAs of the assistance systems [173]. In addition, the moment when participants look at the left side mirror can also possibly influence RoA, which is limited by using an acoustic signal triggering the look at the left side mirror to provide similar temporal gaze sequences [173].

Complementary to Lane changes Decision Aid Systems providing mainly warning functions with the consideration of traffic safety, the developed MBLCDAS considers additionally driver uncertainty and supports drivers during the decision-making process, which is usually beyond the typical warned range of risks or dangers detected by current LCDAS [173]. Moreover, as the developed MBLCDAS adapts to drivers’ uncertainty states, it is treated by drivers as a “partner” [173]. It is expected to understand driver uncertainty and support drivers with recommendations for lane change decisions during decision-making in lane change maneuvers.
6 Conclusion

6.1 Summary of Thesis

As a complex and highly dynamic driving task, the lane change maneuver is considered as one of the most dangerous driving maneuvers [56]. It requires drivers to integrate highly dynamic information from different sources to make a safe decision and to perform the maneuver safely in a timely manner. Driver uncertainty about the current situation can substantially prolong this decision-making process [119], potentially leading to dangerous lane change maneuvers. Regarding traffic safety, it is therefore essential to consider driver uncertainty while developing lane change assistance systems. In addition, the information that existing lane change assistance systems provide to drivers is not adaptive to the drivers’ uncertainty states during decision-making in the current situation. This non-adaptive assistance can be either obtrusive with too many unnecessary advice or too unobtrusive without needed information on time. For instance, when drivers are quite certain about the situation and systems still provide information actively, the interaction with such systems can be annoying and even disturbing. When drivers are uncertain during the decision-making process and systems provide no helpful information on time, the interaction with the systems will not be beneficial. Such non-adaptive aids may have an impact on drivers’ mental models of the system functionality [124] and further decrease drivers’ trust in assistance systems [17]. As a consequence, it causes the disuse of systems [116]. Hence, besides traffic safety, it is also important to build driver trust in automation with the consideration of driver uncertainty while developing lane change assistance systems.

Inspired by the “emancipation” theory of trust stating humans tend to trust in their partners when they are uncertain in social interaction [170] and transferring it to the context of the human machine interaction, it is assumed that drivers tend to build trust in systems and avoid the occurrence of system disuse, when assistance systems consider driver uncertainty and help shorten the decision-making process and the decision times accordingly. Based on this assumption, this dissertation aimed at developing a Model-Based Lane Change Decision Aid System (MBLCDAS) integrating driver uncertainty during decision-making in its interaction strategy for lane change maneuvers. The MBLCDAS adapts its information behavior to the drivers’ uncertainty states: Information will be given in an active way when drivers are uncertain during decision-making and information will be presented unobtrusively when drivers are certain [171]. This adaptive assistance can help to build appropriate trust in the assistance system and also provide traffic safety [173].

To develop the proposed MBLCDAS, driver uncertainty during decision-making has been first studied in a driving simulator for specific lane change scenarios on two-lane motorways: The subject vehicle drives in the right lane, approaching a slower vehicle in the same lane, while a third vehicle in the left lane is approaching the subject vehicle [175]. The distance gap, closing speed, and time to collision
(TTC) between the subject vehicle and the approaching vehicle are varied and found to significantly influence driver uncertainty. Driver uncertainty is measured by reaction times, subjective uncertainty scores and action proportion for lane change decisions [175]. Information on current traffic situations concerning distance gap, closing speed and the resulting TTC between the subject vehicle, the lead vehicle, and the approaching vehicle is collected with a frequency of 60 Hz in the driving simulator with 29 participants.

The collected information is then used to develop a probabilistic model of driver uncertainty, which can recognize drivers’ uncertainty states as either “certain” or “uncertain” in a given lane change situation [172]. Regarding the structure of the model, Tree-Augmented Naive (TAN) Bayesian is selected among the candidate models (full Bayesian classifier, naive Bayesian classifier, TAN classifier) with the highest Bayesian information criterion (BIC) score [172]. Based on the mutual information, \(TTC_A\) (respectively \(TTC_B\)) and \(G_A\) (respectively \(G_B\)) that separately represent the TTC between the subject and the lead vehicle (respectively the approaching and the subject vehicle), the distance gap between the subject and the lead vehicle (respectively the approaching and the subject vehicle) are selected as attributes for the model of driver uncertainty. Based on the Kullback-Leibler Divergence, the collected subjective uncertainty scores from the driving simulator experiment are mapped onto the conceptualized two uncertainty states of the model. With the selected attributes and the mapped drivers’ uncertainty states, the conditional probability of the driver uncertainty can be inferred in a given lane change situation after structure and parameter learning [172]. The model of driver uncertainty is evaluated with test data, showing an average accuracy of approx. 0.78 [172].

With the help of the decision thresholds, the outputs of the model can be classified into one of the drivers’ uncertainty states as either “certain” or “uncertain” [171]. In addition, the recommendation for lane change decisions is classified by a safety analysis as either “decision for changing the lane” or “no lane changes decision” with the help of the action threshold between the subject and the approaching rear vehicle [171]. The classified driver uncertainty states provided by the model and the classified lane change decisions offered by the decision recommendation together trigger the Human Machine Interface (HMI) via symbols representing criticality and driver uncertainty [171]. Emotional faces are chosen for the symbols, which consist of the dimensions of colors and emotional expressions: Colors are used to describe both the criticality and driver uncertainty, while the emotional expressions are used to provide recommendations for lane change decisions [171].

After implementing the model of driver uncertainty and the corresponding HMI of the proposed MBLCDas in the driving simulator, an evaluation study with 20 participants has been conducted, where the MBLCDas is compared with other reference systems with respect to the reduction of reaction times and the building of trust [173]. The results show that all systems including MBLCDas are able to reduce reaction times in comparison to the driving without any assistance [173]. In addition, trust has been built in the MBLCDas [173]. Compared to other reference systems without considering driver uncertainty, MBLCDas is reported to be most accepted and trusted by participants [173].

6.2 Contributions

- The investigation of driver uncertainty during decision-making in lane change maneuvers in the driving simulator has especially contributed to identifying factors that influence driver
uncertainty during decision-making. It fills the gap of studying driver uncertainty in the lane change driving task and helps extend the understanding of drivers’ lane change behaviors.

- The developed model of driver uncertainty can recognize the drivers’ uncertainty states during decision-making in lane change maneuvers, which supplements the driver model specific to lane change maneuvers.

- As a supplement to the current lane change assistance systems focusing on safety aspect with provided warnings for potential dangers, the developed MBLCDAS additionally adapts its information behavior to driver uncertainty during decision-making. It can provide drivers with helpful suggestions actively when they are uncertain during decision-making, and gives useful suggestions for lane change decisions in a conservative way when drivers are already certain in the decision-making process.

- The used human factors approach that combines the experimental methodology and Bayesian network modeling can be transferred to other domains to help build trust between humans and machines. It can further help design adaptive driver assistance systems and offer design suggestions for developing trustworthy assistance systems.

- Inspired by the “emancipation” theory of trust from social psychology, trust has been built in the proposed MBLCDAS that adapts to driver uncertainty in lane change maneuvers, which has been demonstrated by an evaluation study. Building driver trust by adapting to driver uncertainty provides a new way to build trust in automation, which supplements the theory of trust in automation.

### 6.3 Open Issues and Future Work

Although expected results have been achieved, there are still many limitations and open issues that can be considered in future work:

- The investigation of driver uncertainty in lane change maneuvers considers main factors that influence drivers’ decision-making process in lane change maneuvers such as TTC, distance gap, and closing speed. However, other factors related to drivers such as driver age, gender, type or other environmental factors may also have a potential impact on driver uncertainty, which needs to be further studied and identified in future.

- The experiments have been conducted in the driving simulator and participants need to follow a strict experimental procedure, which to some extent may impair the drivers’ natural driving experience. Apart from this, although participants have expressed that the experienced lane change scenarios in the driving simulator are quite similar to their experiences on motorways, the difference between the use of the driving simulator and field studies on real roads is still supposed to exist, which may needs to be taken in to account in future work.

- The target and recruited participants in experiments are mostly college students, which are relatively very young and therefore it is unsure whether they can represent driver uncertainty in general and if there is an extreme change of driver uncertainty between young drivers and old drivers, which needs further investigation in future.
• In the experiment, driver uncertainty is measured by reaction times and subjective uncertainty scores, which has been empirically proven to reflect driver uncertainty. However, regarding the dynamic development of driver uncertainty, the used measures cannot help measure driver uncertainty continuously. It implies that possible physical measurements that may cope with this issue are needed in future.

• In the experiment, subjective uncertainty scores for a given lane change scenario are collected for the model’s inputs. The developed model of driver uncertainty is static, as it is difficult to continually measure driver uncertainty in the driving simulator. It means that the model of driver uncertainty cannot change with time and reflect the negative relationship between reaction times and driver uncertainty. To solve this problem, a dynamic Bayesian network of driver uncertainty can be considered in the future work.

• Although the developed MBLCDAS is reported to be adaptive to drivers’ uncertainty states by some participants, there are also many participants complaining about the non-adaptability of the proposed MBLCDAS. As driver uncertainty is actually individually different, it is necessary to investigate driver uncertainty considering the group factors such as driver age, gender, etc. Following the trend of personalization for the development of ADAS, the development of lane change assistance systems are also expected to be personalized to satisfy different individuals’ requirements in future.

• As the interface design is a necessary part, but not the main focus of this work, the proposed interface design is one possible design for the developed MBLCDAS. Besides the used smiley symbol, other visual cues or modalities can be also considered to adapt to the model of driver uncertainty for the interface. In addition, the effect of displays on the building of trust also needs to be studied in future.

• In the evaluation study, although the use of game controller can help to measure reaction times precisely, it is reported by participants that driving without using the steering wheel is not naturalistic. Instead, buttons on the steering wheel can be considered to measure reaction times in the future study.

• Regarding the commercial use, the developed MBLCDAS can be used in specific lane change scenarios at the moment, which needs to be generalized for all lane change scenarios in the future work.
A Informed Consent

A.1 Study I
Einverständniserklärung zur Teilnahme am Experiment

„Klassifikation des Fahrerzustands beim Spurwechsel im Fahrsimulator“

Projekt CSE_ Car that Cares (WP1_Task3_Experiment1)

Liebe Studienteilnehmer,


Zusammenfassungen der Daten (gemittelt über die Teilnehmer) werden anonymisiert in Textform, beispielsweise in wissenschaftlichen Artikeln publiziert und fließen in die Fahrermodellierung des Projektes CSE ein.

Sie können sich jederzeit und ohne Nennung von Gründen aus der Studie zurückziehen. Sollten Sie Fragen haben, beantworten wir sie gerne. Vielen Dank, dass Sie mit ihrer Zeit unsere Arbeit und damit die Forschung im Bereich der Fahrerassistenzsystementwicklung unterstützen!

1) Ich bin bereit an dieser Studie im Rahmen des Projekts teilzunehmen
2) Ich wurde über die Ziele der Studie aufgeklärt. Ich fühle mich ausreichend informiert.
3) Mir wurde erklärt, dass:
   a. während der Studie digitale Aufzeichnungen gemacht werden,
   b. alle persönlichen Informationen unter das Bundesdatenschutzgesetz\(^1\) fallen, was bedeutet, dass meine Identität nicht ohne meine Einwilligung preisgegeben wird,
   c. alle gesammelten Daten ausschließlich und anonymisiert für wissenschaftliche Zwecke im Rahmen dieser Arbeit verwendet werden,
   d. ich jederzeit und ohne Begründung eine Aktivität oder die gesamte Teilnahme an der Studie abbrechen kann.
4) Ich kann die wissenschaftlichen Mitarbeiterin Fei Yan\(^2\) kontaktieren, wenn ich Fragen zur Evaluation, dem Projekt oder meiner Teilnahme habe.


\(^2\) M.Sc. Fei Yan, OFFIS, Escherweg 2, 26121 Oldenburg, 0441/9722-139, yan@offis.de
Ich habe die Teilnahmeinformationen aufmerksam gelesen und bin damit einverstanden, dass meine Kontaktdaten gespeichert werden und die Ergebnisse der Studie anonymisiert in wissenschaftlichem Kontext veröffentlicht werden kann.

Oldenburg, den __________ Unterschrift _________________________
A.2 Study II
Einverständniserklärung zur Teilnahme am Experiment

„Klassifikation des Fahrerzustands beim Spurwechsel im Fahrsimulator“

Projekt CSE_ Car that Cares (WP1_Task3_Experiment 2)

Liebe Studienteilnehmer,


Zusammenfassungen der Daten (gemittelt über die Teilnehmer) werden anonymisiert in Textform, beispielsweise in wissenschaftlichen Artikeln publiziert und fließen in die Fahrermodellierung des Projektes CSE ein.

Sie können sich jederzeit und ohne Nennung von Gründen aus der Studie zurückziehen. Sollten Sie Fragen haben, beantworten wir sie gerne. Vielen Dank, dass Sie mit ihrer Zeit unsere Arbeit und damit die Forschung im Bereich der Fahrerassistenzsystementwicklung unterstützen!

1) Ich bin bereit an dieser Studie im Rahmen des Projekts teilzunehmen
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\(^1\) http://bundesrecht.juris.de/bundesrecht/bdsg_1990/gesamt.pdf
\(^2\) M.Sc. Fei Yan, OFFIS, Escherweg 2, 26121 Oldenburg, 0441/9722-139, yan@offis.de
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Oldenburg, den __________ Unterschrift _________________________
A.3 Evaluation Study
Einverständniserklärung zur Teilnahme am Experiment

„Untersuchung des Vertrauens in Spurwechsel Assistenz System II“

Projekt CSE_Car that Cares

Liebe Studienteilnehmer,


Zusammenfassungen der Daten (gemittelt über die Teilnehmer) werden anonymisiert in Textform, beispielsweise in wissenschaftlichen Artikeln publiziert und fließen in die Fahrermodellierung des Projektes CSE ein.

Sie können sich jederzeit und ohne Nennung von Gründen aus der Studie zurückziehen. Sollten Sie Fragen haben, beantworten wir sie gerne. Vielen Dank, dass Sie mit ihrer Zeit unsere Arbeit und damit die Forschung im Bereich der Fahrerassistenzsystementwicklung unterstützen!

1) Ich bin bereit an dieser Studie im Rahmen des Projekts teilzunehmen
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   c. alle gesammelten Daten ausschließlich und anonymisiert für wissenschaftliche Zwecke im Rahmen dieser Arbeit verwendet werden,
   d. ich jederzeit und ohne Begründung eine Aktivität oder die gesamte Teilnahme an der Studie abbrechen kann.
4) Ich kann die wissenschaftlichen Mitarbeiterin Fei Yan\(^2\) kontaktieren, wenn ich Fragen zur Evaluation, dem Projekt oder meiner Teilnahme habe.

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Oldenburg, den __________ Unterschrift _________________________
B  Demographic Questionnaire
Angabe zusätzlicher statistischer Daten zum Experiment
„Untersuchung des Vertrauens in Spurwechsel Assistenz System II“
Projekt CSE_ Car that Cares

Alter: __________
Geschlecht: __________
Führerschein seid ___ Jahren
Geschätzte Kilometer pro Jahr: ______________
Brillenträger: __________

Müssen Sie aufgrund einer Erkrankung regelmässig Medikamente einnehmen? Wenn ja, tragen Sie diese bitte unten ein?

_______________________________________________________________
_______________________________________________________________
_______________________________________________________________
_______________________________________________________________
C Instruction

C.1 Study I
Allgemeine Informationen zum Experiment im Fahrsimulator
„Klassifikation des Fahrerzustands beim Spurwechsel im Fahrsimulator“

Projekt CSE: Car that Cares (WP1_Task3_Experiment1)

Liebe Teilnehmerin, lieber Teilnehmer,

vielen Dank, dass Sie an unserem Experiment zur Klassifikation des Fahrerzustands beim Spurwechsel teilnehmen. Dieses Experiment findet im Rahmen eines vom Land Niedersachsen geförderten Forschungsprojektes statt, in dem es um die Modellierung und Simulation des Fahrerverhaltens auf Autobahnen geht.

Ablauf und Aufgabe der Versuchspersonen


1. Wenn Sie die Lücke zwischen Ihnen und dem Auto im Rückspiegel als zu klein für Ihren Spurwechsel empfinden, bremsen Sie bitte (Bremspedal bitte mindestens halb durchtreten).
2. Wenn Sie die Lücke als ausreichend empfinden, lenken Sie bitte nach links (Lenkrad etwa 45° einschlagen).

Sobald Ihre Aktion vom System aufgezeichnet wurde, verschwinden die beiden Fahrzeuge. Geben Sie bitte nun auf der Tastatur rechts neben dem Lenkrad ein, wie sicher Sie sich bei der Entscheidungsfindung für die jeweilige Aktion fühlten (1-5). 1 bedeutet „gar nicht sicher“, 5 bedeutet „sehr sicher“. (Die Sicherheit hier hat nicht mit ihrem guten oder falschen Fahrverhalten zu tun, ist nur eine subjektive
Bewertung für die unterschiedlichen Situationen.) Nach der numerischen Eingabe auf der Tastatur drücken Sie bitte noch die „Enter“ Taste. Nachdem Sie diese Taste gedrückt haben, wird die nächste Situation gestartet.

**Datenaufzeichnung**

Während des Versuches werden Daten der Reaktionszeit aufgezeichnet und anschließend statistisch ausgewertet. Zusätzlich erfasst die Anlage Daten über den Versuchsablauf, das bedeutet wann welche Signale dargeboten wurden. Diese Daten werden nach dem Versuch zusammengeführt und für die Verbesserung eines am OFFIS entwickelten Fahrermodells verwendet, welches für die Simulation von Mensch-Maschine Interaktion genutzt wird. Die im Fahrsimulator aufgezeichneten Versuchsdaten lassen sich nachträglich nicht mit ihren persönlichen Daten in Verbindung bringen, die sie für die Auszahlung des Teilnahmemonorars in unserer Abrechnungsabteilung angeben (siehe Bogen „Stundennachweis der Teilnahme am Simulatorexperiment“). Die Versuchsergebnisse bleiben anonymisiert.

Neben den zur Versuchsdurchführungszeit aufgezeichneten Daten möchten wir einige zusätzliche Daten erfassen (siehe Bogen „Angabe zusätzlicher statistischer Daten“). Diese werden verwendet, um unterschiedliche Gruppierungen von Versuchspersonen zu ermöglichen und entsprechende statistische Auswertungen machen zu können. Ebenso können Alkohol, Nikotin und Medikamente Auswirkungen auf die Experimentergebnisse haben, daher benötigen wir hierzu Angaben.

**Sicherheitshinweise**

Wichtig: Der Simulator verfügt über aktive Ansteuerungen von Lenkrad, Gas- und Bremspedal. Beachten Sie daher folgende Hinweise:

- Fassen Sie das Lenkrad locker mit beiden Händen an, bitte greifen sie nicht von innen in das Lenkrad ein.

Bitte denken Sie daran:

- Sie können das Experiment jederzeit unterbrechen bzw. fortsetzen, wenn Sie es wollen oder sogar abbrechen.
- Bei Ermüdungen können Sie, wann auch immer Sie mögen, eine Pause einlegen.
- Bei körperlichem Unwohlsein oder sonstigen Beschwerden sagen Sie bitte sofort dem Versuchsleiter Bescheid.

**Einverständniserklärung**

Um die Teilnahme am Experiment zu bestätigen unterschreiben Sie bitte die entsprechende Einverständniserklärung.
C.2 Study II
Allgemeine Informationen zum Experiment im Fahrsimulator

„Klassifikation des Fahrerzustands beim Spurwechsel im Fahrsimulator“

Projekt CSE: Car that Cares (WP1_Task3_Experiment 2)

Liebe Teilnehmerin, lieber Teilnehmer,

vielen Dank, dass Sie an unserem Experiment zur Klassifikation des Fahrerzustands beim Spurwechsel teilnehmen. Dieses Experiment findet im Rahmen eines vom Land Niedersachsen geförderten Forschungsprojektes statt, in dem es um die Modellierung und Simulation des Fahrerverhaltens auf Autobahnen geht.

Ablauf und Aufgabe der Versuchspersonen


Ihre Aufgabe ist es nun möglichst zügig einen Überholvorgang durchzuführen. Wenn Sie den Überholvorgang möglich finden, lenken Sie bitte nach links (Lenkrad etwa 45° einschlagen). Falls dies nach Ihrer Einschätzung nicht möglich ist, bremsen Sie bitte (Bremspedal bitte mindestens halb durchtreten). Bitte verhalten Sie sich dabei so, wie sie es im normalen Straßenverkehr auch tun würden und behalten Sie ihren üblichen Fahrstil bei.

Sobald Ihre Aktion vom System aufgezeichnet wurde, verschwinden die beiden Fahrzeuge. Geben Sie bitte nun auf der Tastatur rechts neben dem Lenkrad ein, wie sicher Sie sich bei der Entscheidungsfindung für die jeweilige Aktion fühlten (1-5). 1 bedeutet „gar nicht sicher“, 5 bedeutet „sehr sicher“. (Die Sicherheit hier hat nicht mit ihrem guten oder falschen Fahrverhalten zu tun, ist nur eine subjektive
Bewertung für die unterschiedlichen Situationen.) Nach der numerischen Eingabe auf der Tastatur drücken Sie bitte noch die „Enter“ Taste. Nachdem Sie diese Taste gedrückt haben, wird die nächste Situation gestartet.

**Datenaufzeichnung**

Während des Versuches werden Daten der Reaktionszeit aufgezeichnet und anschließend statistisch ausgewertet. Zusätzlich erfasst die Anlage Daten über den Versuchsablauf, das bedeutet wann welche Signale dargeboten wurden. Diese Daten werden nach dem Versuch zusammengeführt und für die Verbesserung eines am OFFIS entwickelten Fahrermodells verwendet, welches für die Simulation von Mensch-Maschine Interaktion genutzt wird. Die im Fahrsimulator aufgezeichneten Versuchsdaten lassen sich nachträglich nicht mit ihren persönlichen Daten in Verbindung bringen, die sie für die Auszahlung des Teilnahmehonorars in unserer Abrechnungsabteilung angeben (siehe Bogen „Stundennachweis der Teilnahme am Simulatorexperiment“). Die Versuchsergebnisse bleiben anonymisiert.

Neben den zur Versuchsdurchführungszeit aufgezeichneten Daten möchten wir einige zusätzliche Daten erfassen (siehe Bogen „Angabe zusätzlicher statistischer Daten“). Diese werden verwendet, um unterschiedliche Gruppierungen von Versuchspersonen zu ermöglichen und entsprechende statistische Auswertungen machen zu können. Ebenso können Alkohol, Nikotin und Medikamente Auswirkungen auf die Experimentergebnisse haben, daher benötigen wir hierzu Angaben.

**Sicherheitshinweise**

Wichtig: Der Simulator verfügt über active Ansteuerungen von Lenkrad, Gas- und Bremspedal. Beachten Sie daher folgende Hinweise:

- Fassen Sie das Lenkrad locker mit beiden Händen an, bitte greifen sie nicht von innen in das Lenkrad ein.

Bitte denken Sie daran:

- Sie können das Experiment jederzeit unterbrechen bzw. fortsetzen, wenn Sie es wollen oder sogar abbrechen.
- Bei Ermüdungen können Sie, wann auch immer Sie mögen, eine Pause einlegen.
- Bei körperlichem Unwohlsein oder sonstigen Beschwerden sagen Sie bitte sofort dem Versuchsleiter Bescheid.

**Einverständniserklärung**

Um die Teilnahme am Experiment zu bestätigen unterschreiben Sie bitte die entsprechende Einverständniserklärung.
C.3 Evaluation Study
Liebe Teilnehmerin, lieber Teilnehmer,

vielen Dank, dass Sie an unserem Experiment „Untersuchung des Vertrauens in Spurwechselassistentenzsysteme II“ teilnehmen. Dieses Experiment findet im Rahmen eines vom Land Niedersachsen geförderten Forschungsprojektes statt, in dem es um die Modellierung und Simulation des Fahrerverhaltens auf Autobahnen geht.


Sie fahren in dem Versuch entweder ohne System oder mit den Systemen (System A, B, C, D).

Instruktion für OHNE System


Allgemeine Informationen zum Experiment im Fahrsimulator

„Untersuchung des Vertrauens in Spurwechselassistentenzsysteme II“

Projekt CSE: Car that Cares (WP1_Task3_Experiment 4)

Instruktion für MIT System


D Handouts for the Evaluation Study
System A

Der Spurwechsel ist möglich, bitte lenken Sie nach links.

Der Spurwechsel ist nicht möglich, bitte bremsen.
System B

Der Spurwechsel ist möglich, bitte lenken Sie nach links.

Der Spurwechsel ist nicht möglich, bitte bremsen.
System C

In den Situationen die Entscheidung zu **Lenken** typischerweise **einfach** zu treffen ist.

In den Situationen die Entscheidung zu **Lenken** typischerweise **schwierig** zu treffen ist.

**Der Spurwechsel ist nicht möglich, bitte bremsen.**
System D

Der Spurwechsel ist möglich, bitte lenken Sie nach links.

Der Spurwechsel ist möglich, bitte lenken Sie nach links.

Der Spurwechsel ist nicht möglich, bitte bremsen.
E Trust Questionnaires for the Evaluation Study
Fragebogen : System A

Im Folgenden finden Sie eine Liste von Aussagen für die Bewertung des Vertrauens zwischen Fahrer und Spurwechselassistenzsystem A. Sie sollen die Intensität Ihres Gefühls auf mehreren Skalen bewerten. Bitte zeichnen Sie ein "x" in jeder Zeile an der Stelle, die am besten zu Ihrem Gefühl oder Ihren Eindruck beschreibt. (Anmerkung: überhaupt nicht zustimmen = 1; völlig einverstanden = 7).

1. Das System A verhält sich in einer verständlichen Art und Weise.
   ![Score Scale]

2. Ich bin zuversichtlich bei System A.
   ![Score Scale]

3. Das System A ist zuverlässig.
   ![Score Scale]

4. Das System A bietet bei Spurwechsel eine ausreichende Verkehrssicherheit.
   ![Score Scale]

   ![Score Scale]

   ![Score Scale]

   ![Score Scale]

8. Das System A hat getan, was von mir erwartet worden ist.
   ![Score Scale]

9. Ich akzeptiere das System A.
   ![Score Scale]

    ![Score Scale]

11. Insgesamt vertraue ich dem System A.
    ![Score Scale]

Ich vertraue dem System, weil es ____________________________________________
Weitere Gründe, dem System zu vertrauen: (aus den folgenden Optionen bitte ankreuzen, mehrere Kreuze möglich):

A: Es passt sich verschiedenen Situationen an.

B: Es ist nicht störend.

C: Ich glaube, dass es intelligent ist.

D: Es versteht mich.
Fragebogen: System B

Im Folgenden finden Sie eine Liste von Aussagen für die Bewertung des Vertrauens zwischen Fahrer und Spurwechselassistenzsystem A. Sie sollen die Intensität Ihres Gefühls auf mehreren Skalen bewerten. Bitte zeichnen Sie ein "x" in jeder Zeile an der Stelle ein, die am besten zu Ihr Gefühl oder Ihren Eindruck beschreibt. (Anmerkung: überhaupt nicht zustimmen = 1; völlig einverstanden = 7).

1. Das System B verhält sich in einer verständlichen Art und Weise.

2. Ich bin zuversichtlich bei System B.

3. Das System B ist zuverlässig.

4. Das System B bietet bei Spurwechsel eine ausreichende Verkehrssicherheit.

5. Mit dem System B kann ich schnell alle Spurwechselmanöver erledigen.

6. Ich fühle, dass System B mich gut verstehen kann.

7. System B gibt mir rechtzeitig nützliche Vorschläge, wenn ich Schwierigkeiten habe, bei einem Überholmanöver Entscheidungen zu treffen.

8. Das System B hat getan, was von mir erwartet worden ist.

9. Ich akzeptiere das System B.

10. Ich folge den Vorschlägen von System B lieber als meiner eigenen Einschätzung.

11. Insgesamt vertraue ich dem System B.

Ich vertraue dem System, weil es

_____________________________________________________________________________
Weitere Gründe, dem System zu vertrauen: (aus den folgenden Optionen bitte ankreuzen, mehrere Kreuze möglich):

A: Es passt sich unterschiedlichen Situationen an.
B: Es ist nicht störend.
C: Ich glaube, dass es intelligent ist.
D: Es versteht mich.
Fragebogen: System C

Im Folgenden finden Sie eine Liste von Aussagen für die Bewertung des Vertrauens zwischen Fahrer und Spurwechselassistenzsystem A. Sie sollen die Intensität Ihres Gefühls auf mehreren Skalen bewerten. Bitte zeichnen Sie ein “x” in jeder Zeile an der Stelle, die am besten zu Ihr Gefühl oder Ihren Eindruck beschreibt. (Anmerkung: überhaupt nicht zustimmen = 1; völlig einverstanden = 7).

1. Das System C verhält sich in einer verständlichen Art und Weise.

2. Ich bin zuversichtlich bei System C.

3. Das System C ist zuverlässig.

4. Das System C bietet bei Spurwechsel eine ausreichende Verkehrssicherheit.


7. System C gibt mir rechtzeitig nützliche Vorschläge, wenn ich Schwierigkeiten habe, bei einem Überholmanöver Entscheidungen zu treffen.

8. Das System C hat getan, was von mir erwartet worden ist.

9. Ich akzeptiere das System C.


11. Insgesamt vertraue ich dem System C.

Ich vertraue dem System, weil es ___________________________________________
Weitere Gründe, dem System zu vertrauen: (aus den folgenden Optionen bitte ankreuzen, mehrere Kreuze möglich):

A: Es passt sich unterschiedlichen Situationen an.
B: Es ist nicht störend.
C: Ich glaube, dass es intelligent ist.
D: Es versteht mich.
Fragebogen: System D

Im Folgenden finden Sie eine Liste von Aussagen für die Bewertung des Vertrauens zwischen Fahrer und Spurwechselassistenzsystem A. Sie sollen die Intensität Ihres Gefühls auf mehreren Skalen bewerten. Bitte zeichnen Sie ein "x" in jeder Zeile an der Stelle ein, die am besten zu Ihr Gefühl oder Ihren Eindruck beschreibt. (Anmerkung: überhaupt nicht zustimmen = 1; völlig einverstanden = 7).

1. Das System D verhält sich in einer verständlichen Art und Weise.

2. Ich bin zuversichtlich bei System D.

3. Das System D ist zuverlässig.

4. Das System D bietet bei Spurwechsel eine ausreichende Verkehrssicherheit.


8. Das System D hat getan, was von mir erwartet worden ist.

9. Ich akzeptiere das System D.


11. Insgesamt vertraue ich dem System D.

Ich vertraue dem System, weil es ______________________________________________
Weitere Gründe, dem System zu vertrauen: (aus den folgenden Optionen bitte ankreuzen, mehrere Kreuze möglich):

A: Es passt sich unterschiedlichen Situationen an.
B: Es ist nicht störend.
C: Ich glaube, dass es intelligent ist.
D: Es versteht mich.
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